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Business Analytics Maturity Frameworks: A Systematic Literature Review

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Abstract
In the current digital era, data and analytics are the triggers for business performance and competitive advantage. Data analytics, however, require the right set of capabilities that aid the organisations to leverage upon the analytics initiatives and excel in the competitive world. A large number of researchers, consultants and academicians have proposed different business data analytics models that are ready-to-use models, helpful for organisations to assess and utilise data analytics within their organisations. However, before adopting any model or creating any customised model, it is important to understand the key capabilities that derive business analytics maturity. This research aims to study and assess the existing Business analytics models, to derive these key capabilities. A total of 15 models from real-world, theoretical models and consultancy-led models are studied, and on the basis of key factors in each model, the key capabilities required to enhance business analytics are identified. It is found that every organisation needs four key capabilities, namely, leadership, information technology, human capital and organisation, to assess the business analytics maturity in their firms. Though the findings are made on the basis of thorough analysis of existing maturity models, further investigation is needed to identify the variables that may be relevant for different industries and countries.

Keywords: Business analytics, Maturity models, Business Intelligence

Introduction

The last decade has witnessed significant growth in business analytics (BA), marking a revolution in the discipline of business analytics (Davenport & Harris, 2007). Schoemaker & Tetlock (2017) defined business analytics as computing large datasets to derive meaningful insights to facilitate business decision-making and gain an edge over competitors. The organizations are relying on business intelligence and analytics systems for making data-driven decisions (Rouhani et al., 2016). The organizations integrate the physical organizational infrastructure, data sets, and intelligent structures, and apply the analytical capabilities, to reap the advantage of business analytics (Sharda, Helen & Turban, 2020). The use of business analytics by businesses is often associated with many business advantages, including superior organisational performance (Ramakrishnan, Jones & Sidorova, 2012), financial gains (AT Kearney, 2019), refined business processes, innovative-oriented work culture, improved supply chain, better predictive capabilities and efficient marketing and sales initiatives (Grover et al., 2018). Another study by Saravanabhavan, Raman & Maddulety (2020) provides that the implementation of business analytics models by organizations provides them with numerous benefits in the sphere of finance, operations, sales, and strategy.

It is largely recognized that business analytics is known to be evolving the fate of organizations, which spurs them to adopt different business analytical models. However, to fetch the benefits of business analytics, organizations are required to possess the right set of capabilities to exploit the analytical infrastructure and tools (LaValle et al., 2011). One of the ways to exploit the same is by leveraging the analytical maturity model of the organizations. The study by Becker, Knackstedt & Pöppelbuß (2009) defines the analytical maturity model as the framework that helps managers find the capabilities required for driving the initiatives for business analytics.

The importance of maturity models stems from the fact that they help identify the current organizational analytical status and help identify the required capabilities to improve organizational performance (Röglinger, Pöppelbuß & Becker, 2012). That is, the maturity models guide the organizations to move from the current to the desired state, by understanding the existing capabilities, aiding in transformation, and developing new capabilities, by initiating a change process (Wendler, 2012).

The current literature provides many business maturity models, which can be classified as generic or specific. According to Blondiau, Mettler & Winter (2016), the generic BA models can be utilized in any industry or business, while the specific BM models are designed to serve the intrinsic of a particular industry, as per the nature of the business. Though all the different MA models are developed for different purposes, the key similarity entails exploring the existing and needed capabilities to achieve the desired state by the organization.

Although the literature presents a large number of analytical maturity models, there is no synchronization or standardization in these models (Cosic, Shanks & Maynard, 2015; Tavallaei et al., 2015), which can guide the organizations to understand the key capabilities required for attaining maturity. Thus, the aim of this paper is to study different existing maturity models for assessing the analytical maturity of organisations and find out the key capabilities required by the organisations to derive their analytical maturity.

Materials & Methods

The study will make use of a systematic literature review in which the existing BA models as propounded by the consultants and academicians are assessed. The key factors of different models are assessed, with the aim of determining the capabilities that are common to these models. A total of 15 BA models have been studied, which include real-world models, theoretical resource-based models, business intelligence models, and consulting-led models. Some of the models that are considered for analysis include the Delta Plus Model (Davenport, 2018); DAMM model (Association Analytics, nd); BLAST analytics Maturity Framework (Król & Zdonek, 2020); Analytics Maturity Quotient Framework (Król, Karol & Zdonek, 2020); Business Analytics Capability Framework (Cosic et al., 2015); Analytic Process Maturity Model (Grossman, 2018); Web Analytics Maturity Model (Hamel, 2009); HP BI Maturity Model (Hewlett-Packard, 2007); TDWI BI maturity model (TDWI, 2009); Gartner BI maturity model; Enterprise BI Maturity Model (Chuah and Wong, 2012); McKinsey model; Kearney Model; Cap Gemini Predictive Analyst maturity framework assessment (CapGemini, 2017); and SAS Analytics Maturity Framework.

Each of these models is studied to understand the steps and variables that make the model. Thereafter, the key capabilities of all these models are mapped to find the common factors, which shape the core capabilities and key findings for this study.

Maturity Models

The summary of fifteen maturity models that are considered in this study is summarized in Table 1.

Table 1: Summary of Maturity Models

S.no	Model Name	Reference	Category
1.	Delta Plus	Thomas Davenport	Real World Models
2.	DAMM – Data Analytics Maturity Model for Associations	Association Analytics	Real World Models
3.	Blast Analytics Maturity Framework	Blast Analytics & Marketing	Real World Models
4.	Analytics Maturity Quotient (AMQ) Framework	Aryng LLC	Real World Models
5.	Business Analytics Capability Framework (BACF)	Cosic	Theoretical Model
6.	Analytics Process Maturity Model (APMM)	Grossmann, R.L	Theoretical Model
7.	Web Analytics Maturity Model	Hamel, S	Theoretical Model
8.	HP BI Maturity Model	HP	BI Maturity Model
9.	TDWI Analytics Maturity Model	TDWI, Halper, F.,	BI Maturity Model

		Stodder, D.	
10.	Gartner's maturity model for Data & Analytics	Gartner, Inc	BI Maturity Model
11.	Enterprise BI model	Chuah & Wong	BI Maturity Model
12.	McKinsey Analytics Maturity Model	McKinsey	Analytics Consulting Model
13.	Kearney Analytics Maturity Model	A.T. Kearney	Analytics Consulting Model
14.	Cap Gemini Analytics Maturity Model	Cap Gemini Inc	Analytics Consulting Model
15.	SAS Analytics Maturity Framework	SAS Institute Inc	Analytics Consulting Model

Delta Plus Model

This analytical maturity model is proposed by Thomas Davenport & Harris, derived from the practical organizational experiences, on how the analytics capabilities are built (Davenport, 2005). This model is an enhancement to the earlier DELTA model proposed by Davenport (2005, 2010). Under this model, the five stages of Analytics Maturity are enhanced and asserted that meaningful analytics are created by ensuring that the data is organized well, unique in nature, well-integrated, easily accessible, and of superior quality (Devenport, 2018). Davenport further asserts that data integration across different organizational silos is important, along with combining the transactional systems across different strategic business units. Furthermore, the key elements or capabilities that form the essence of this model are high-quality data, enterprise orientation to manage analytics, analytical leadership, strategic targets, and analysts. The author also added two additional variables to the DELTA model, namely technology and analytics techniques (Davenport, 2018). These two elements are spurred by the development of new techniques, like big data, machine learning, artificial intelligence, cloud, and open source.

This model fosters assessment of the organizational analytical maturity on these seven elements. The ratings of the analytical maturity are performed on a scale ranging between 1.00 to 5.99 points, and the organization holds a place on any one of the analytical continuum stages (as given in Figure 1).

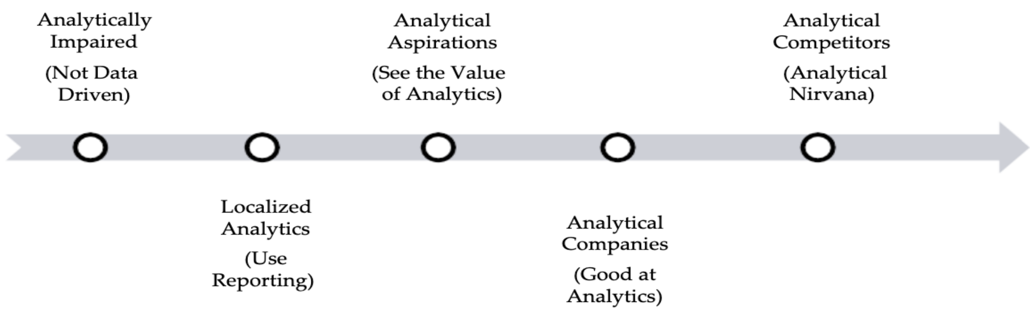

Figure 1: Analytics Continuum- Delta Plus Model

Source: Davenport, 2018

Under the first analytically impaired phase, the organizations operate on intuitions, with no future plans to go analytical. Localised Analytics, is the second phase, in which data reported is operated back-end, without any cooperation between management levels for the use of data analytics. The third stage is analytical aspirations, in which the organizations recognize the importance of data analytics, but progress toward implementation is slow. The fourth stage is analytical companies, and the organizations lying at this stage make effective use of data analytics but fail to strategically align it completely. The final stage is analytical competitors, in which the organizations operate on an analytics strategy and use it to secure a competitive advantage (Davenport, 2018).

Data Analytics Maturity Model for Associations (DAMM)

The DAMM model has been developed by Association Analytics with the aim of investigating the place held by the organization as it takes a data-guided approach to create the overall organizational analytical strategy. This model assumes the importance of four key elements, namely, Organization and Culture, Architecture/Technology, Data governance, and Strategic alignment. Based on the assessment of the organization on these four elements, the association is placed on one of the five phases of analytical maturity, as given in Figure 2.

Figure 2: Data Analytics Maturity Model – DAMM

Source: Król & Zdonek, 2020

The first is the learning stage, in which the organizations are not aware of analytics benefits. Data is siloed and institutions are used for decision-making. There is no dedication of team members to utilizing data analytics. In the planning stage, the organization though understands the benefits of analytics, is still not using it. However, they keep a future vision towards leveraging data analytics in their organizations. The third stage is the building stage, in which the organization chalks out a robust data analytics implementation strategy. some of the aspects covered in this stage are drawing data strategy, personnel planning, and gaining an understanding of the output buildouts. In the application stage, the organizations deploy the analytics, and the outcomes are tracked using key performance indicators (KPIs) and performance dashboards, to find the consequences of the data analytics. The final stage is the leading stage, in which the organization attains the pinnacle of analytical maturity level and the decisions are led by data and analytics.

BLAST Analytics Maturity Framework

The BLAST Analytics Maturity Framework has been proposed by Hamel and encompasses five dimensions of maturity, namely culture, capability, technology, data and process (Król & Zdonek, 2020). The framework proposes the use of assessment, interviews, key findings and strategic roadmap to plan and evolve the maturity journey within an organisation. By providing scoring on each of the success factors, the organisations can define their state of maturity, ranging from nascent, developing, proficient and advanced. The framework of the model is presented in Figure 3.

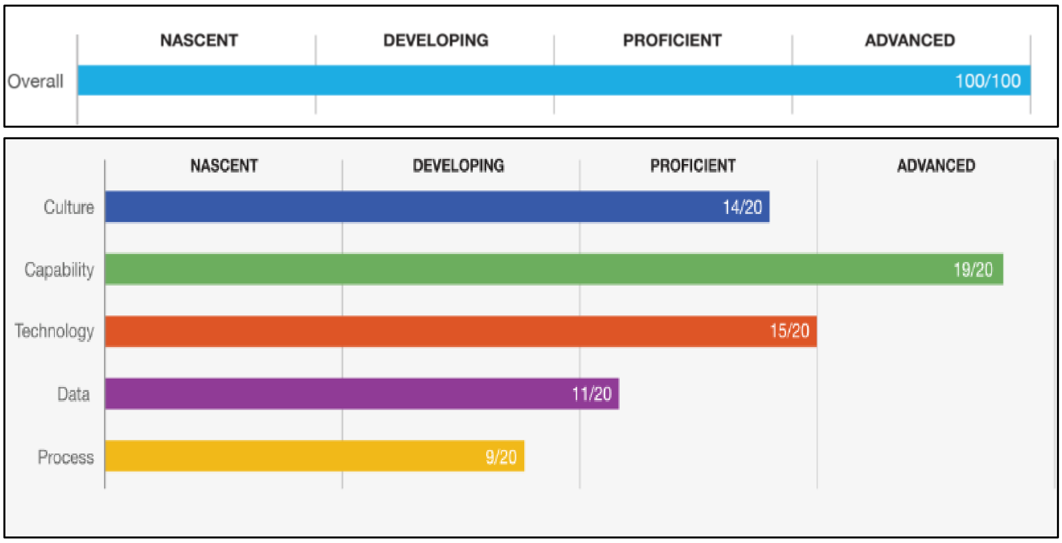

Figure 3: Blast Analytics Maturity Framework

Source: Blast Analytics, nd

The scoring of each of the capabilities shows that capability possesses the maximum weight, while the process holds the minimum weightage in determining the maturity level, as per this model.

Analytics Maturity Quotient Framework (AMQ)

This model utilises the five capabilities of data quality (DQ), data-driven leadership (L), people with analytical skills (P), data-driven decision-making process (D) and infrastructure (I), for assessing the maturity of the organisation (Król & Zdónek, 2020). Data quality is important since the quality of data determines the ability the learn about their customers and products. Data-driven adds to organisational leadership utilises the data over their beliefs in factoring in growth opportunities. People with analytics skills possess the right analytical and technical skills, which help them analyse data for business processes and tasks. Next, data-driven decision-making processes are used by data-driven leaders and people with analytical skills to make use of data and turn them into relevant decisions. Finally, agile infrastructure supports the other capabilities.

In mathematical terms the formula used to calculate maturity is

$$AMQ = DQ \times (0.4\times L + 0.3\times P + 0.2\times D + 0.1\times I)$$

The equation shows the weightage of importance for each of the capabilities, which signifies that data quality holds the highest value, while agile infrastructure is the lowest.

Values for the factors are continuous, for example, poor levels of leadership in an organization could be 1 or 2 and strong levels could be 9 or 10. Similarly, lack of analytics talent could be 1, 2 and medium levels of talent could be 5, 6.

Business Analytics Capability Framework (BACF)

The Business Analytics Capability Framework (BACF) model has been proposed by Cosic, with the aim of determining the existing level of business analytics (Cosic et al., 2015). The model encompasses four key capabilities areas for maturity, namely Governance, Culture, Technology and people and a number of capabilities are defined for each of these areas, as presented in Figure 4.

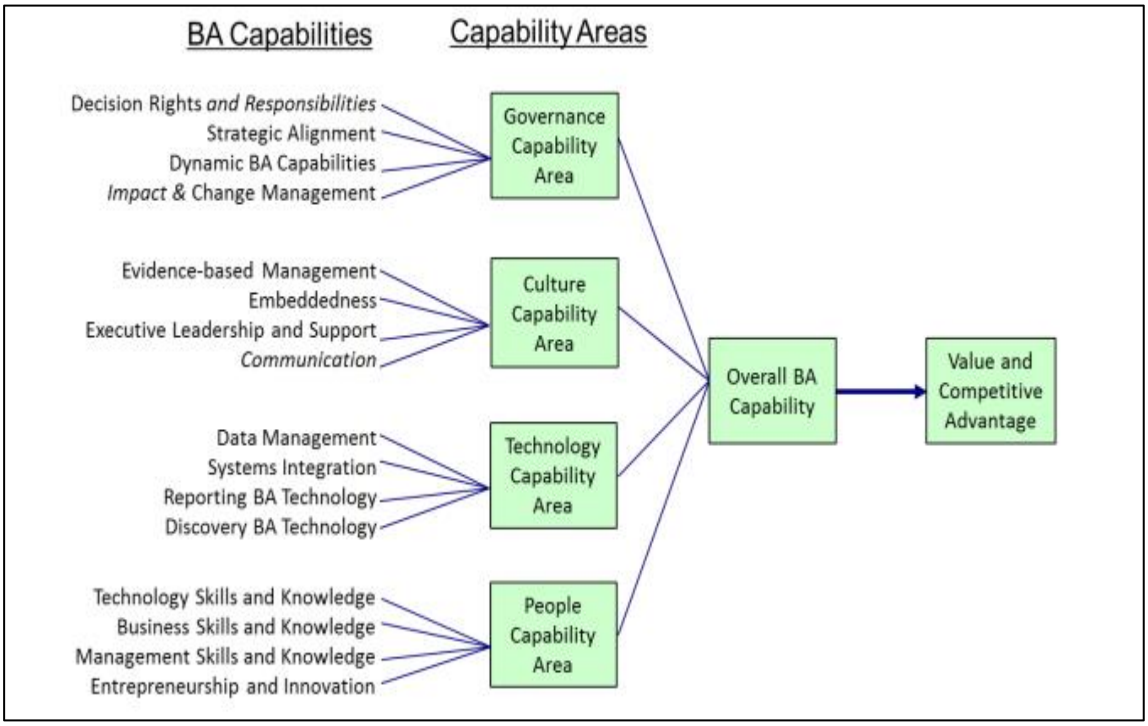

Figure 4: Business Analytics Capability Framework BACF

Source: Cosic et al, 2015

It has been asserted that the BA capability is built by embracing these four capabilities, which becomes a source of competitive advantage for the organisations. The model also comprises a five-level scale in maturity that ranges from non-existent to optimisation. The low-level capabilities mentioned in this scale are strategic alignments, change management, leadership, agility, system integration, data management and skills and knowledge.

Analytics Process Maturity Model (APMM)

The APMM model has been propounded by Grossman (2018), under which the key capabilities for attaining maturity are categorised into six heads, namely to build analytical models, deploy the built model, manage and operate analytic infrastructure, protect analytic assets through appropriate policies and procedures, operate an analytic governance structure and identify analytic opportunities, make decisions, and allocate resources based upon an analytic strategy. The model is presented in Figure 5.

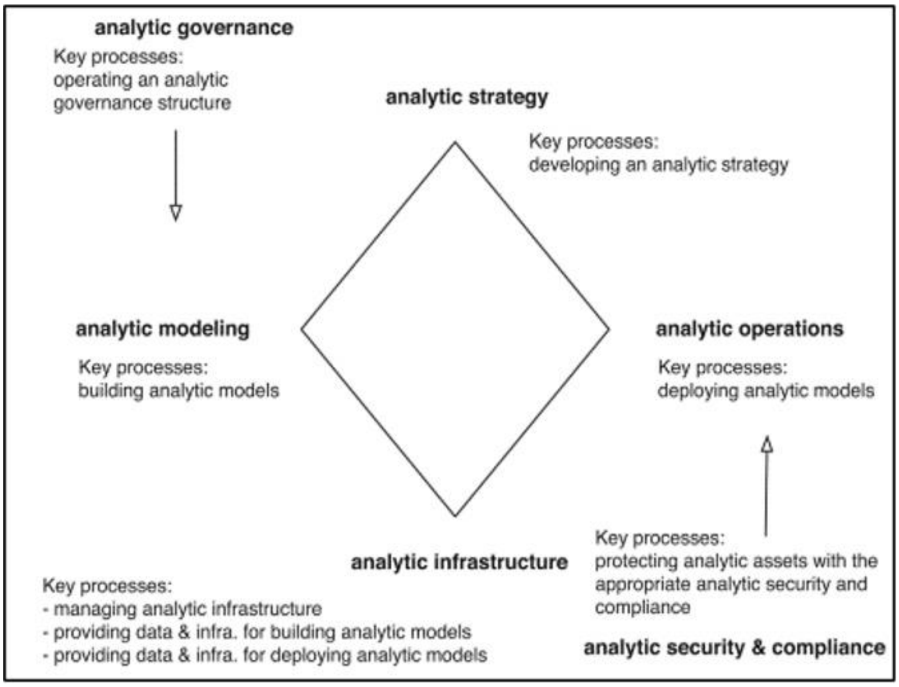

Figure 5: Analytics Process Maturity Model

Source: Grossman (2018)

Based on the utilisation of these capabilities, the firms are defined on the basis of five-level maturity levels. These levels are defined as being able to build reports; able to build and deploy models; presence of repeatable processes to build and deploy analytics; consistency in enterprise-wide processes for analytics; and strategy-driven enterprises (Grossman, 2018).

Web Analytics Maturity Model

The Web Analytics Maturity Model (WAMM) is proposed by Hamel (2009), which basically aims to assess the organisational capabilities of businesses in the digital space. The key capabilities proposed by this model are leadership support (given by the management, governance and adoption), defining objectives, scoping, talent (analytics team and expertise), Process (Continuous Improvement Process and Analysis Methodology) and Information technology (Tools, technology and data integration). The model is presented in Figure 6.

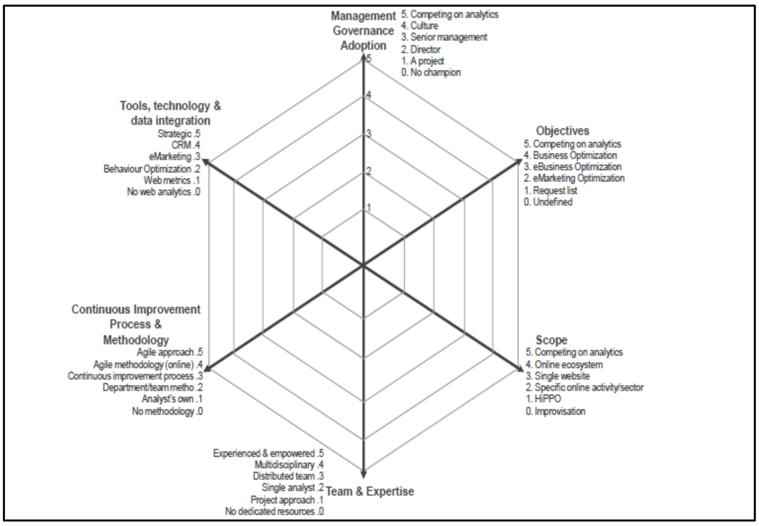

Figure 6: Web Analytics Maturity Model

Source: Hamel, 2009

Each of these dimensions of the capabilities is rated between 0 to 5, and based on the overall scoring, the organisation takes the position (lowest to highest) from analytical impaired, initiated, operational, integrated, competitive and addicted (Hamel, 2009).

HP BI Maturity Model

The HP BI maturity model has been developed by Hewlett Packard (2007) which defines organisational maturity on the basis of three dimensions: business enablement, information management strategy and program management. The business enablement dimension concerns the advancing business needs and problems that business intelligence solutions solve. The information technology dimension is concerned with advancing information solutions to serve emerging business needs. The strategy and program management dimension, finally, deals with the advancing managerial skills required, which emerges as an important enabler and catalyst for business intelligence success.

By utilising these capabilities or dimensions, the model proposes that the organisation can excel through five stages of business maturity, by gaining continuous improvement and empowerment (Figure 7).

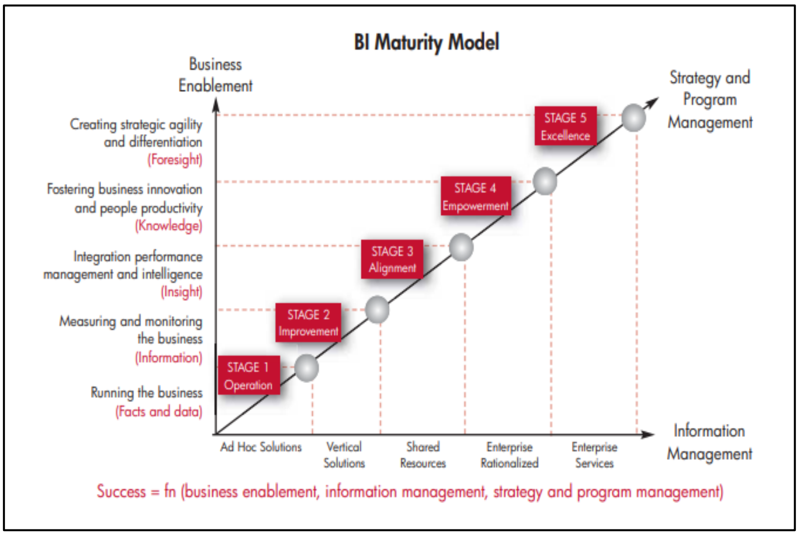

Figure 7: HP BI Maturity Model

Source: 101.com

The key factors that encompass this model are performance management, integration, strategic agility and shared resources.

TDWI Analytics Maturity Model

The TDWI BI model is concerned with implementing Business Intelligence by investing money and value, and in turn, leads to a gain in market share (TDWI Research, 2009). The model encompasses five dimensions that guide organisations to accelerate the level of BI maturity, namely organisation, infrastructure, data, analytics and governance (Figure 8).

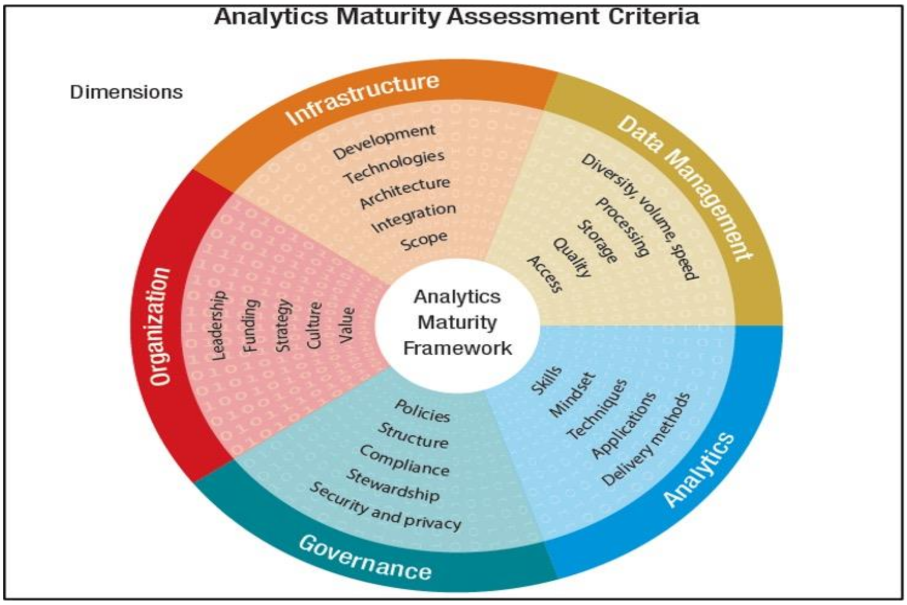

Figure 8: TDWI Analytics Maturity Model

Source: TDWI Research, 2015

The organisation dimension discusses the organisational strategy, culture, leadership and funding, that is supportive to implement analytics in the firm. The infrastructure dimension relates to the adequacy of the technologies, architecture, tools and processes that support the maturity initiatives within the enterprise. The data management dimension studies the ability of the firm to manage the variety, velocity, veracity and volume of data, and the strength of the data strategy of the firm. The analytics dimension assesses the organisational analytical culture and analyses the level of analytics used by the organisation. Finally, the governance dimension evaluates the presence of a strong governance process that supports the data and analytics initiatives undertaken by the management (TDWI Research, 2015).

Based on the level of implementation of these capabilities, the organisations can move from different stages of maturity, from nascent, pre-adoption, early adoption, corporate adoption and fully mature (Figure 9).

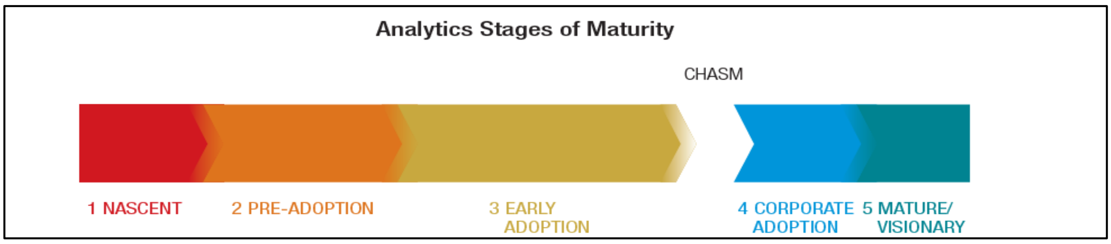

Figure 9: Analytics stages of Maturity

Source: TDWI Research, 2015

This model helps the organisation to move from a business driver to a market driver.

Gartner's Maturity Model for Data & Analytics

Gartner has proposed a business intelligence maturity model, wherein the organisational maturity is assessed along three dimensions, namely people, processes and technology. The model further specifies five stages on which the analytical maturity of the organisations is assessed, namely basic, opportunistic, systematic, differentiating and transformational (Meulen & McCall, 2018) (Figure 10).

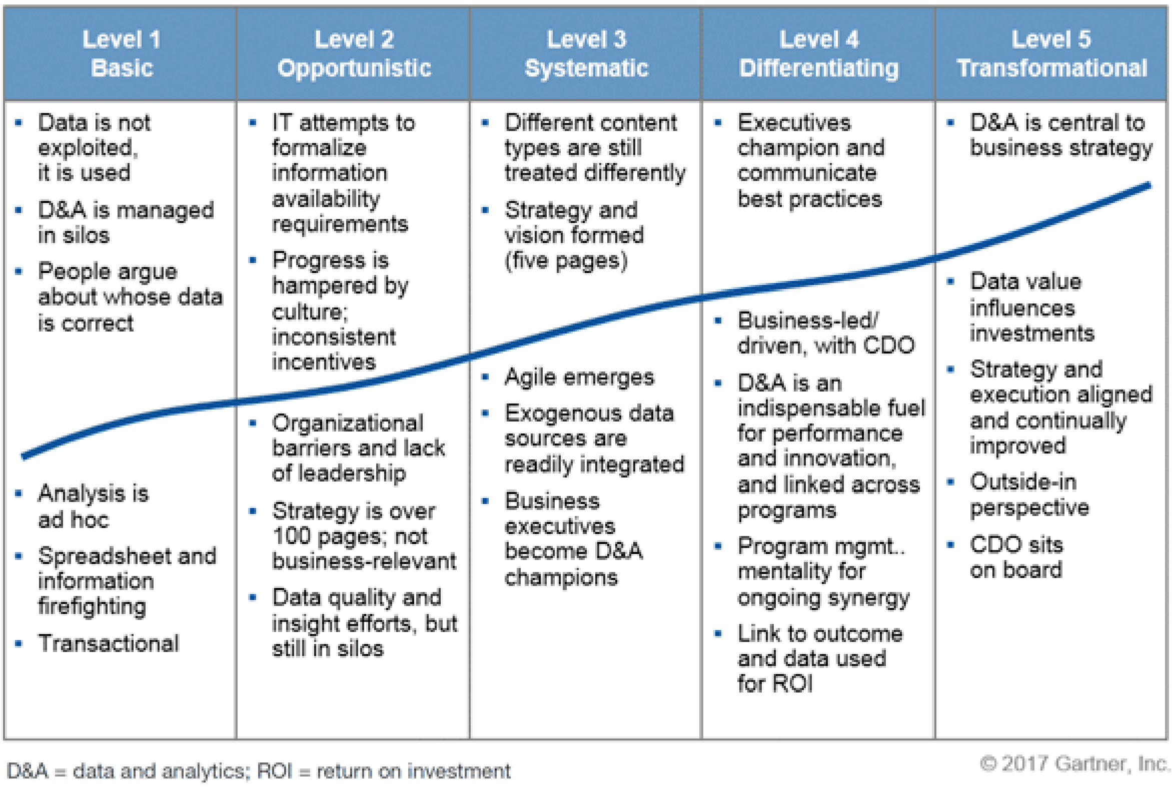

Figure 10: Gartner's Model for Data and Analytics

Source: Meulen & McCall, 2018

In the basic stage, the organisation does not have any real BI capabilities, the data lies inconsistent across different departments and the managers fail to identify the business drivers and understand the information management structure. In the opportunistic stage, specialised managers are hired who utilise data to make tactical decisions, while the data is stored all over the organisation, and transparency about whose data is right is missing. The systematic stage encompasses the strong commitment of the organisational towards business intelligence, with well-defined metrics, but lacks a formal link between organisational objectives, leading to inconsistency in departmental goals. In the differentiating stage, business intelligence governs the strategic objectives, with effective integration with business processes. However, the organisation suffers from an imbalanced organisational structure, aligned with business objectives and strategy. Finally, in the transformative stage, BI strategy and agility are interwoven with the business processes, and systems, and decisions are made based on information that leads to proper analysis (Meulen & McCall, 2018).

The maturity of the BI is enhanced with the changes in the business model, management's vision and data management system of the organisation.

Enterprise BI model

The Enterprise BI maturity model has been developed by Chuah and Wong (2012) with the aim of bridging the gap between academia and industry in the development of BI. This model has two representations, namely staged and continuous. The model has a total of five dimensions on which the analytical maturity levels of the organisation are based, starting from initial to optimising. Progressing through different stages of maturity contributes to continuous improvement in the process. (Figure 12).

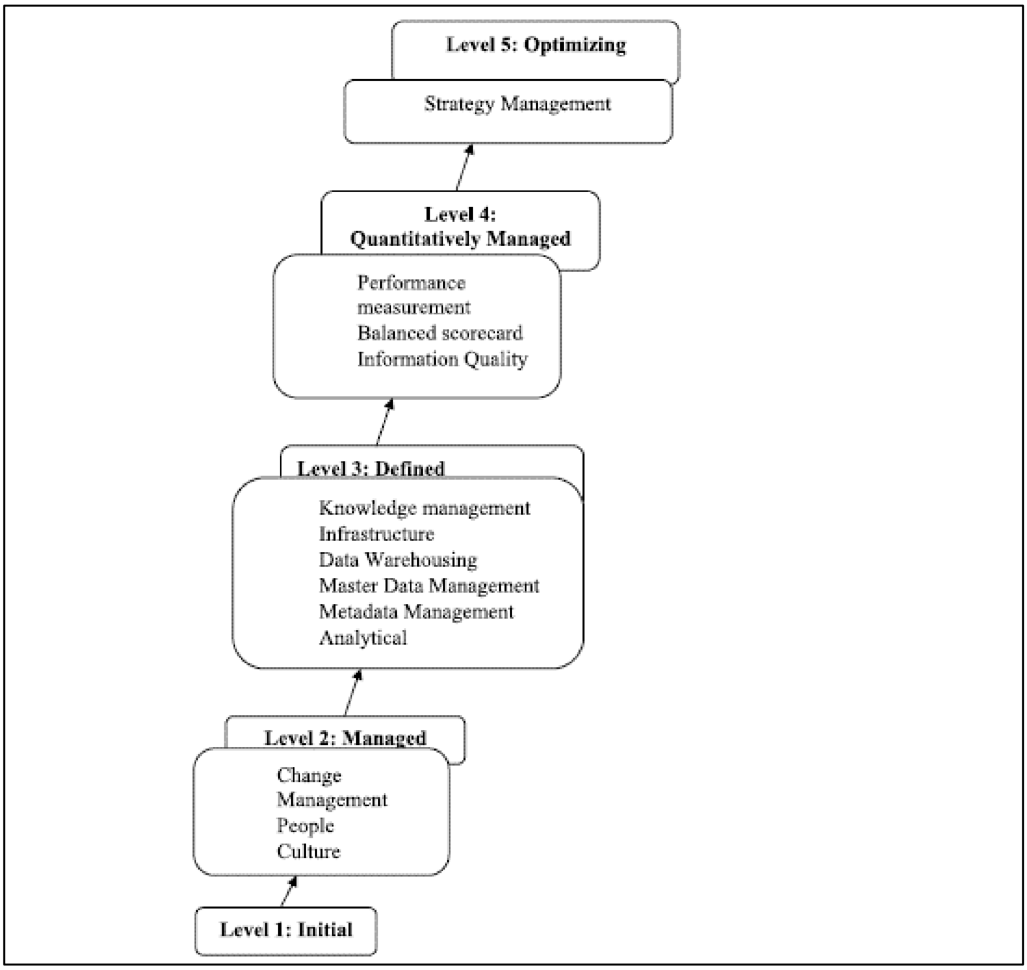

Figure 11: Enterprise BI Maturity Model

Source: Chuah & Wong, 2012

Each of these stages further encompasses different dimensions, namely data warehouse, information quality and knowledge process. The EBI2M model furthers seven dimensions for assessing business maturity level, namely data warehousing, master data management, metadata management, analytical, infrastructures, performance management, and balanced scorecard.

McKinsey Analytics Maturity Model

McKinsey developed a consultancy-led model to determine the analytical maturity levels within an organisation (Henke et al., 2016), which purports several dimensions to assess the state of maturity of the organisation. These dimensions are use cases, data, analytics modelling, process management and culture (Figure 12). Use cases are concerned with selecting the right use cases that help realise the value of the analytics. Data determines the ability of the organisation to manage the data ecosystem, by integrating the internal with the external data. Analytical modelling is the skills and capabilities that mine the data by using advanced analytics. Process management helps make analytics pervasive within the organisation. Finally, the adoption of analytical capabilities enhances, with the help of data and an analytical-driven culture.

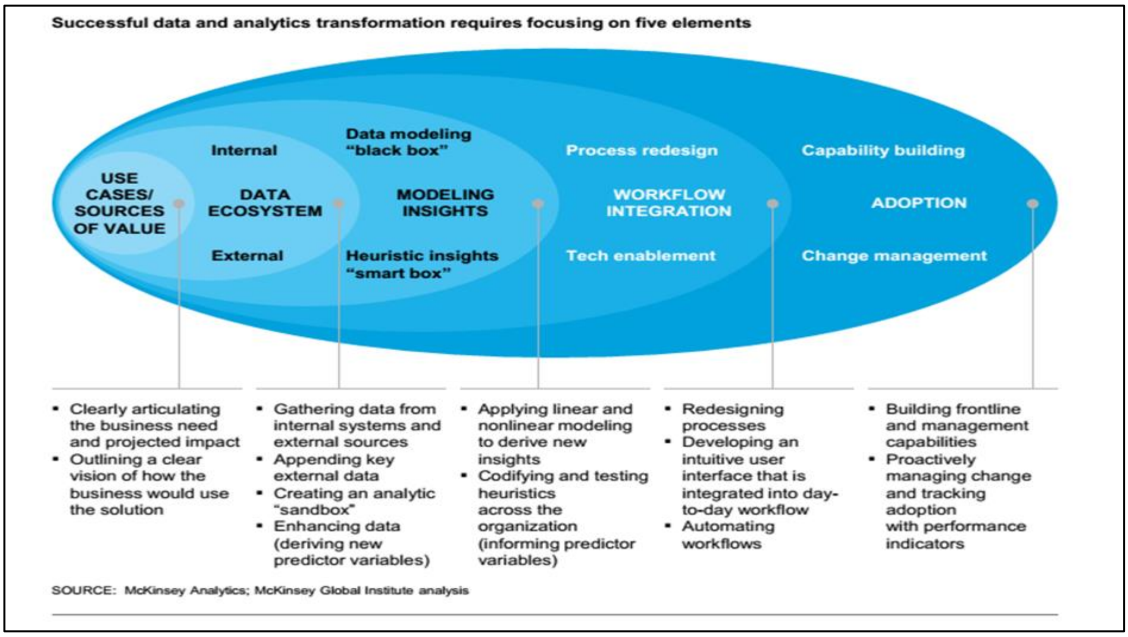

Figure 12: McKinsey Analytics Maturity Model

Source: Miranda, 2018

Kearney Analytics Maturity Model

This model is proposed by AT Kearney, which measures the maturity level in the organisation with the help of four dimensions, namely strategy and leadership, vulture and governance, talent and skills and data ecosystem (Figure 13). Each of these dimensions has further sub-factors, stated as under-

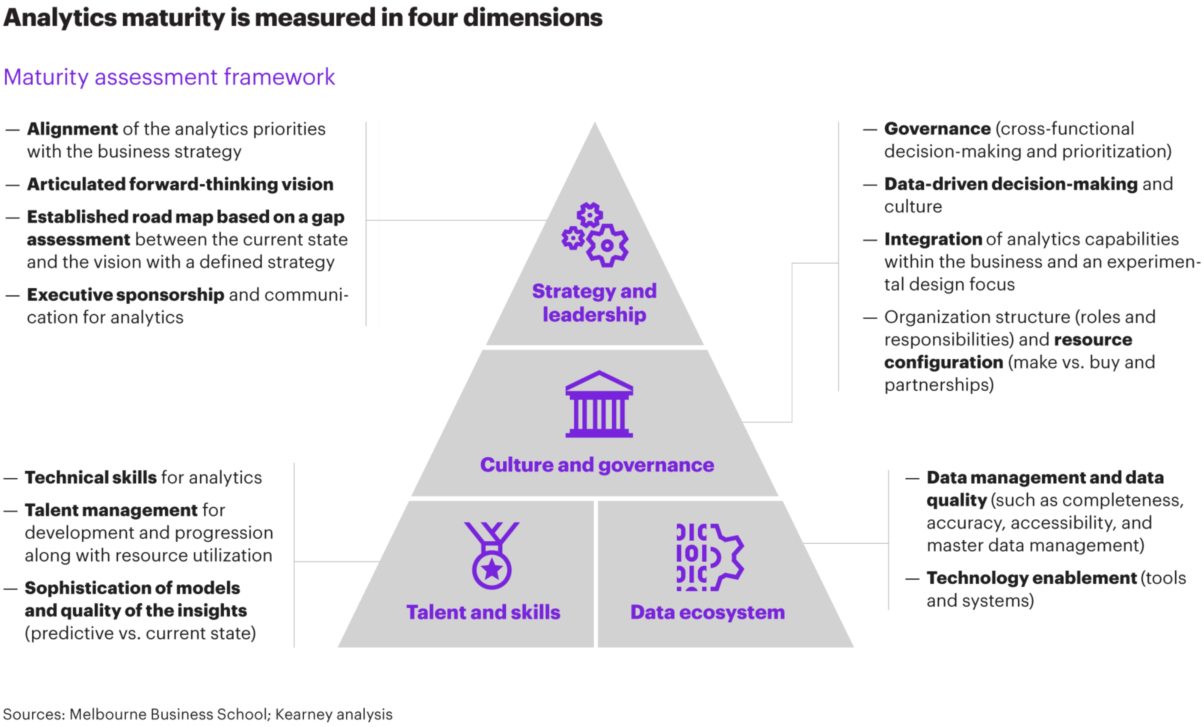

Figure 13: AT Kearney Analytics Maturity Model

Source: Kayande, Rizzon & Khandelwal, 2020

- Strategy & Leadership- this dimension is measured by assessing the alignment between the analytics priorities and business strategy, forward-thinking vision, road map defining the gap between current vision and defined strategy, and executive sponsorship and analytics-related communication.
- Culture and Governance- this dimension is tested by assessing cross-functional decision-making and prioritisation, the culture of data-driven decision-making, integration between analytics capabilities and experimental design focus and organisational structure.
- Talent & Skills- the sub-factors for this dimension include analytics-related technical skills, talent management model sophistication and qualitative insights.
- Data ecosystem- This dimension comprises the elements of data management, data quality and technology enablement.

Capgemini Analytics Maturity Model

This model has been proposed by the consultancy Capgemini (2017) that guides organisations to achieve a comprehensive vision for productive analytics maturity by gaining an understanding of the analytical state. This model measures the analytical maturity of the organisation using five dimensions, namely vision and strategy, enablers, competence, deployment and governance.

Furthermore, the analytical maturity of the organisation is assessed on four levels.

Level 1- Impromptu- This stage is characterised by sporadic and isolated analytical capability, resulting from ad hoc projects.

Level 2- Solo- this stage is further divided into two parts. In the first sub-stage (amateur solo), the predictive analytics are present at the individual level, without the environmental support, the second sub-stage (professional solo), predictive analytics processes and capabilities are integrated with the environment, but operate at the individual level.

Level 3- Ensemble- in this stage, some integration between the departments is observed for the implementation of predictive analytics.

Level 4- Symphony- enterprise-wide predictive analytics operate, which contribute to competitive advantage.

The model is presented in Figure 14-

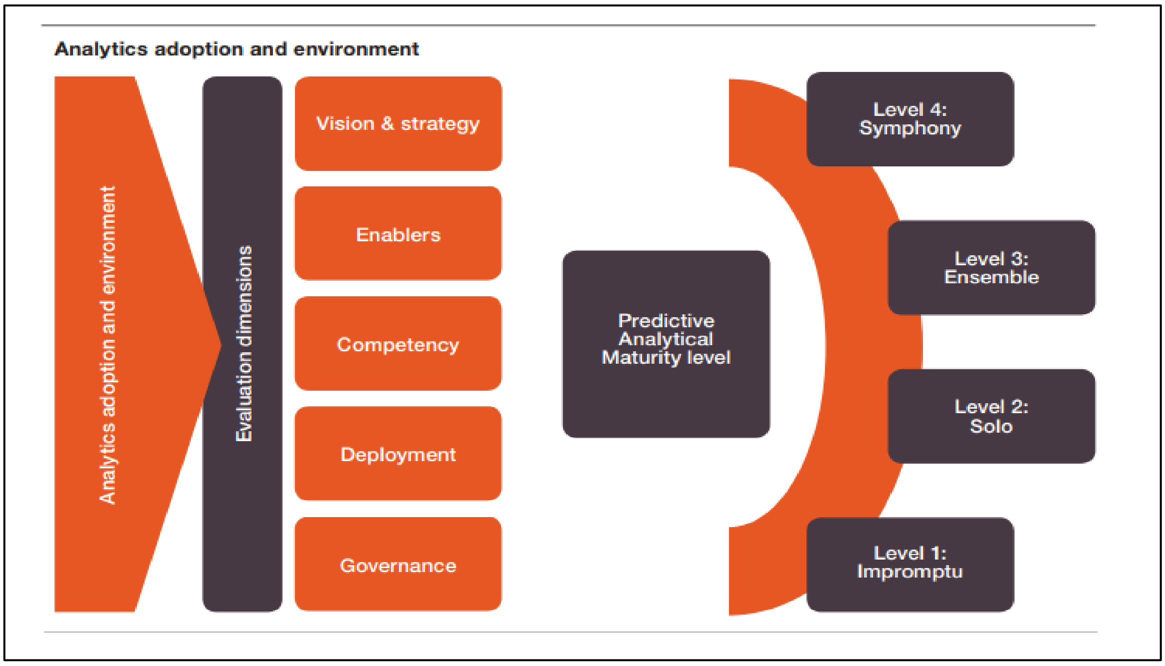

Figure 14: Capgemini Analytics Maturity Model

Source: Capgemini, 2017

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The definition of each of the five dimensions helps define the predictive analytics maturity of the organisation and determine the stage of maturity, based on the criteria presented in figure 15.

	Level 1: Impromptu	Level 2: Solo	Level 3: Ensemble	Level 4: Symphony
Vision and strategy	There is no defined analytics strategy or vision – all development is incidental.	Individuals in some business units may have an analytics vision, but there is no articulated analytics strategy, even for a single business unit.	An analytics vision may have been articulated by individual business units, along with the IT, who have to support the vision.	A well-defined and articulated enterprise-level analytics strategy supports PA initiatives. People, processes and technology are aligned and used optimally.
Enablers	Each business unit can develop ad hoc solutions on its own, or fund groups to build them. There is no standardization of tools/techniques and no data and technology enablers.	Individual business units may collaborate with BI or technology units, but there is very little dialogue.	Some initiatives may see collaboration around data and technology across business units. Some business units share analytics assets and environment.	A formal center of excellence or PA department, or just an informal alliance of PA people, optimizes use of organizational resources. PA environment supports the organization's vision.
Competency	Competency is very low or non-existent.	Individual competency may exist in some business units, but is rarely used more widely.	In some areas, individual competency may have matured into analytic DNA for the business.	Enterprise-wide competency enabling rationalization of initiatives and skills.
Deployment	No integration with operational processes, BI or decision-making systems; some reporting may be enabled.	Integration with operational systems is manual, or a request is made to IT.	Analytics may be integrated with decision-making systems, but not with BI systems.	The technology environment is able to integrate predictive model output with BI, decision systems and operational systems.
Governance	No governance.	Business unit level governance may exist.	Limited enterprise-level governance.	Robust governance ensures enterprise-level review and prioritization of analytics projects.

Figure 15: Definition of dimensions for different analytical maturity levels

Source: Capgemini, 2017

SAS Analytics Maturity Framework

The SAS analytics maturity framework proposes four dimensions to measure the business analytical maturity of an organisation. These dimensions are culture (a culture that is conductive and supports the use of data and analysis for decision-making); internal process readiness; analytical capabilities and data environment. Based on the overall maturity level, the model places the organisation on one of the five maturity stages, as stated in Figure 15.

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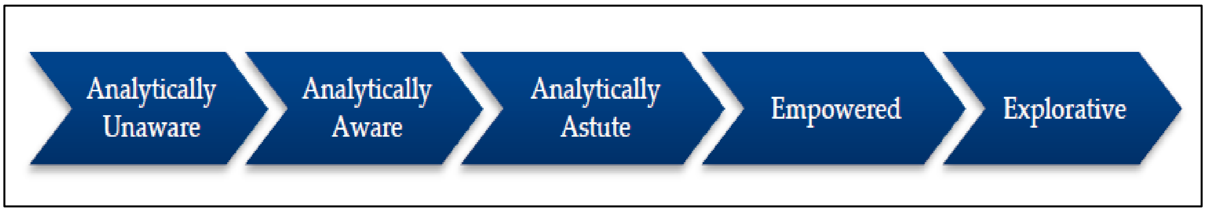

Figure 16: Maturity Stages (SAS analytical maturity framework)

Source: Król & Zdónek, 2020

In the first stage of being ‘analytically unaware’, the organisation makes decisions on their gut feeling without processing any data analytics. In this case, analytical leadership is absent. In the second stage of being ‘analytically aware’, though the managers are aware of data analytics, they make use of data analytics on an ad-hoc basis. The third stage is of being ‘analytically astute’ in which the organisation utilises data analytics, but stays in silos, with fragmented data infrastructure and skills. The ‘empowered’ stage signifies that the organisation makes use of analytics effectively and bases its decisions on the basis of data analysis. Finally, in the explorative phase, the organisation is termed as fully analytically mature, and the use of analytics acts as a strategic differentiator.

Findings

So far, the paper discusses different business maturity analytical models proposed by academicians, researchers and consultants. It is found that all these models assess the organisational analytical maturity level by proposing certain capabilities and dimensions of maturity. Based on the analysis of different business analytical models, the key capabilities of these models are synthesized, given in Table 2.

Table 2: Key Capabilities identified for different global analytical maturity models

S.no	Model Name	Reference	Category	Factors driving Analytics Maturity
1	Delta Plus	Thomas Davenport	Real World Models	Data, Enterprise, Leadership, Targets, Analyst
2	DAMM – Data Analytics Maturity Model for Associations	Association Analytics	Real World Models	Organization & Culture, Architecture/ Technology, Data Governance, Strategic Alignment
3	Blast Analytics Maturity Framework	Blast Analytics & Marketing	Real World Models	Culture, Capability, Technology, Data, Process

4	Analytics Maturity Quotient (AMQ) Framework	Aryng LLC	Real World Models	Data Quality, Leadership, People, Process, Infrastructure (Technology)
5	Business Analytics Capability Framework (BACF)	Cosic	Theoretical Model	Governance, Culture, Technology, People
6	Analytics Process Maturity Model (APMM)	Grossmann, R.L	Theoretical Model	Governance, Strategy, Modelling, Operations, Infrastructure, Security & Compliance
7	Web Analytics Maturity Model	Hamel, S	Theoretical Model	Leadership (Management/Governance/ Adoption), Objectives, Scoping, Talent, Process, IT
8	HP BI Maturity Model	HP	BI Maturity Model	Business Enablement, Information Management, Strategy & Program Management
9	TDWI Analytics Maturity Model	TDWI	BI Maturity Model	Organization, Infrastructure, Data, Governance, Analytics
10	Gartner's maturity model for Data & Analytics	Gartner, Inc	BI Maturity Model	People, Process, Technology
11	Enterprise BI model	Chuah & Wong	BI Maturity Model	Data Warehouse, Master Data Management, Meta Data, Analytics skills, Infrastructure (Technology), Performance Management, Balanced Scorecard
12	McKinsey Analytics Maturity Model	McKinsey	Analytics Consulting Model	Use cases, Data, Analytics Modelling, Process, Culture

13	Kearney Analytics Maturity Model	A.T. Kearney	Analytics Consulting Model	Strategy & Leadership, Culture & Governance, Talent & skills, Data Ecosystem
14	Cap Gemini Analytics Maturity Model	Cap Gemini Inc	Analytics Consulting Model	Vision & Strategy, Enablers, Competence, Deployment, Governance
15	SAS Analytics Maturity Framework	SAS Institute Inc	Analytics Consulting Model	Culture, Process, Capabilities, Data Infrastructure

Source: Author, 2023

From Table 2, it can be observed that all the maturity models are based on building and assessing the analytical maturity levels of the organisations, and the same is tested using different factors, defined as key capabilities.
Furthermore, the frequency of the identified capabilities, as found in different business analytical models is presented, to find out the common analytical capabilities. The frequency of the key identified capabilities is presented in Figure 17.

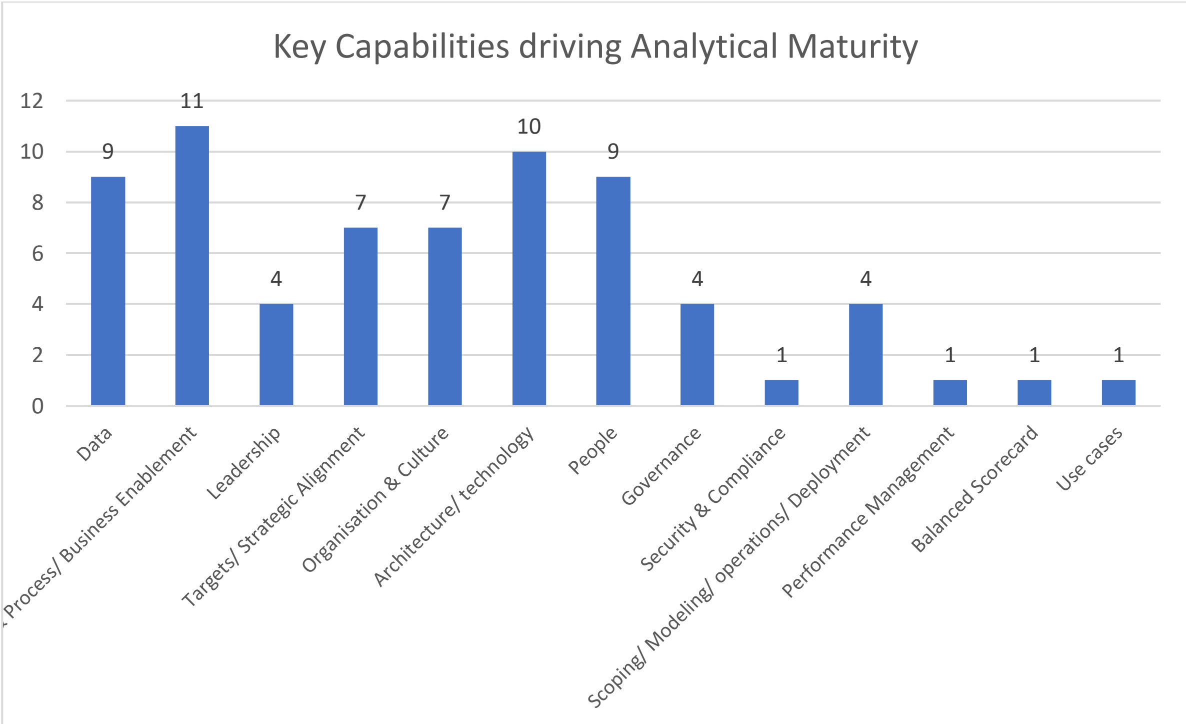

Figure 17: Frequency of key capabilities used in different Analytical Maturity Models

From Figure 17, it can be found that the most common factors and capabilities used by the majority of the existing maturity models are enterprise & process and business enablement, as recognised by 73% of the prevalent maturity models. The second most important factor identified has been architecture and technology, considered important by 67% of all the models. After that, about 60% of the models recognise data and people as the most important variables to drive analytical maturity within organisations. Organisation and culture as well as targets and strategic alignment are embraced by 47% of

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the models each. Governance and operational modelling are recognised by 27% of the models, and some other variables that are considered important (recognised by different models) are security & compliance, performance management, balanced scorecard and use cases.
However, upon closer look, it has been found that many of these variables are interrelated and overlap each other. Thus, to fetch the important and key capabilities, some of these variables are clubbed into four factors which together will constitute the capabilities for the proposed model.

These variables and their sub-factors are presented in Figure 18-

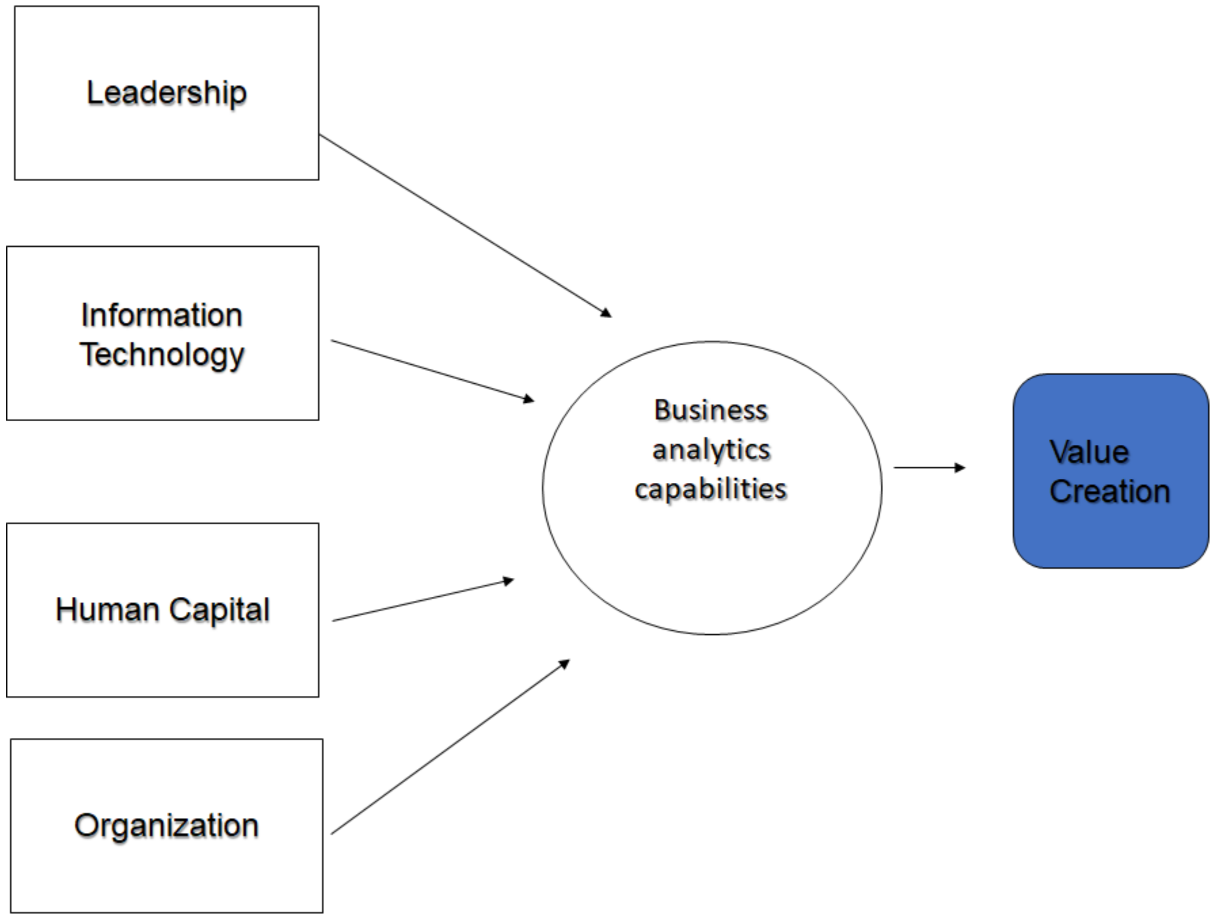

Figure 18: Key Capabilities identified

Leadership = Leadership + Balanced Scorecard + Targets/ Strategic Alignment
Information Technology = Data + Architecture/Technology + Security/ Compliance
Human Capital = People
In total, four capabilities are identified, namely leadership, information technology, human capital and organisation. These four factors are included in most of the above-discussed maturity models. The break down The frequency of these variables included in all these models is further present in Figure 19.

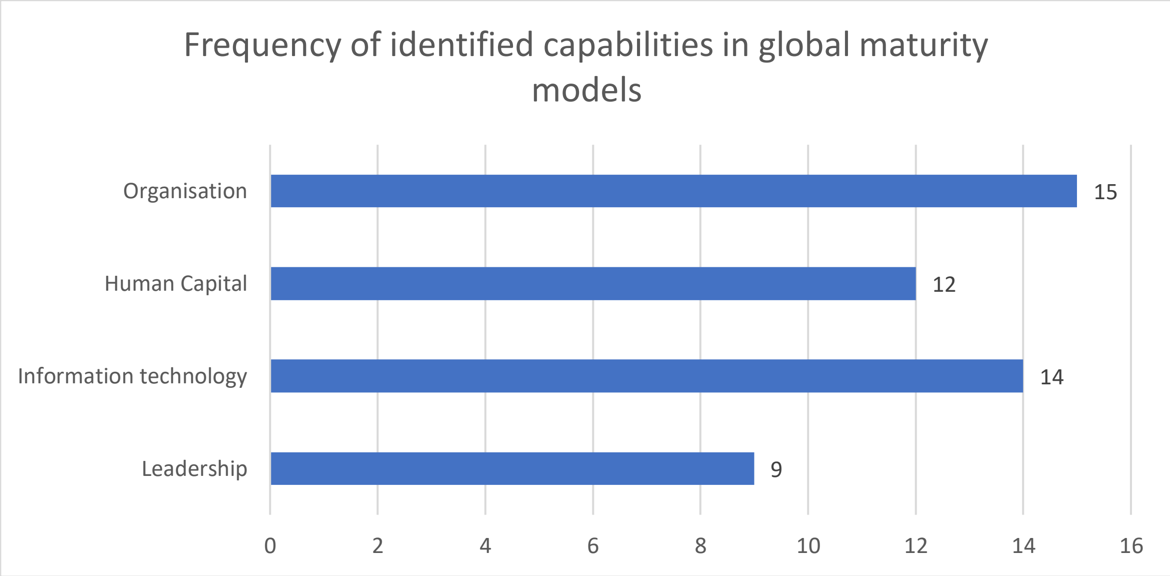

Figure 19: Frequency of identified capabilities in global analytical maturity models

Source: Author, 2023

From Figure 19, it can be found that nearly all the maturity models (100%) state that the organisation is an important variable that helps to assess and drive analytical maturity within the organisations. Information technology is considered the second most important capability, as reported by over 93% of the maturity models. Human Capital are included in 80% of the maturity models studied in this paper. Finally, leadership is rated as a key capability by about 60% of the maturity models. Thus, in light of the importance of these variables, it is suggested that these four capabilities are most vital for assessing and driving analytical maturity within organisations.

Discussion & Conclusion

This research unveils the importance of the use of business analytics maturity towards enhanced business performance and competitive advantage. This necessitates the organisations to adopt or create their own business analytics maturity model, comprising different capabilities. The paper studies the 15 most common and famous maturity models, including real-world, theoretical, BI maturity and analytics consulting models, to explore the key capabilities that are necessary to assess analytical maturity within organisations. It has been found that the four key capabilities that are most frequently used in all these models are Organisation, Information technology, Human Capital and Leadership. Several sub-factors are determined for all these variables, which explain the inclusions in each of these capabilities.

These four capabilities are also deemed vital in the existing literature, from the perspective of deriving organisational analytical maturity. The study by Raber, Winter and Wortmann (2012) suggests that the outlined strategy and vision of the organisation is a major determining factor for analytics maturity. Cosic, Shanks and Maynard (2015) also maintain the importance of the right leadership; while Lauren & Thorlund (2010) render that top and senior managerial support infuses passion for business analytics throughout the organisation. Thus, all these studies stress the importance of leadership skills for implementing analytical maturity capabilities in organisations.

The second key capability derived in this research is information technology, comprising of data, tools and systems. The importance of data is suggested by many studies (Sahay, 2016; United Nations Global Pulse, 2013; Seddon et al., 2012). Both internal and external data are important for efficient management of data (Howson, 2008; Watson & Wixom, 2007). The right tools that help in assessing, managing and analysing the extracted data add to the overall functionality for analytics (Seddon et al., 2012). The business analytics capabilities are efficient with well—integrated operating information systems in the organisation (Myerson, 2002; Shanks, Bekmamedova & Sharma, 2011). Thus, it can be found that information technology is one of the indispensable factors that enhances the overall analytical maturity within organisations.

The third key capability highlighted by the research finding is human capital, formed by talent, skills and competency towards analytical maturity. The study by Ransbotham et al. (2015) suggests that talent leads to competitive advantage by innovating using analytics. Right skillets are needed for analysing and driving insights from the data (McAfee & Brynjolfsson, 2012). In this regard, Cosic et al. (2015) add that skills for translating and communicating analytical insights and values are also vital. The right set of skills includes technical, business, managerial and entrepreneurial for implementing business analytics initiatives in the organisation (Davenport et al., 2010) Vidgen, Shaw and Grant (2017) further emphasise the need for competency to make decisions based on the analysed data. Thus, the human capital of the organisation is important in implementing and leveraging the other capabilities (information technology and organisation) for the benefit of the organisational decision-making.

The organisation is the fourth capability, comprising the elements of process, structure, culture and governance. Krishnamoorthi & Mathew (2018) support this finding, and view that organisation variables contribute positively towards business analytics capabilities, important for enhanced business performance. A study found that analytical models, robust processes, organisational structure and governance contribute to business intelligence and analytics in organisations (Foshay et al., 2015). Governance helps to review the organisational business analytics resources and capabilities for efficiently managing the BA (Shanks et al., 2011). Sharma et al. (2010) identify that well-integrated people and systems, forming an organisational structure are supportive of business analytics. Finally, Hopkins et al. (2010) assert that organisational culture, comprising internal resources, contributes towards business analytics.

Thus, it can be concluded that business analytical maturity is an essence for enhanced business performance, and thus, organisations must deploy different capabilities to accelerate their maturity levels.

Although the paper explores meaningful findings in the area of business analytical maturity, there exist some shortcomings, which require deeper analysis and interpretations. Firstly, though these capabilities are found to be important drivers of analytics maturity, they may not be used as it is in all industries and countries. There may be some industry-related factors and catalysts, which must be recognised and implemented to assess the business analytics maturity in the respective organisations. Secondly, the capabilities are determined based on the existing models, and secondary research. However, some of these models were proposed over a decade ago, but over this time, there have been many changes and dynamism in the business world, thus, making some of these models obsolete. Therefore, further studies can be undertaken by sourcing data and opinions from experienced industry experts and analysts, whose insights can be encapsulated to provide an updated understanding of the key capabilities of business analytics maturity.

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