CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

This chapter presents the extensive review of the literature that was carried out by the researcher on understanding BI&A and its context in India, evolution of BI&A along with the evolving nature and characteristics of data associated, BI&A adoption and implementation, the effectiveness of BI&A, the maturity models developed and used to assess BI&A and the dimensions stated in each model. The multiple dimensions across all the models have been studied in depth. The observations and gaps in research have been identified and highlighted.

Articles published in peer reviewed journals from 2001 to 2019 were accumulated to analyze prior research done in the BI&A area, to analyze BI&A maturity models and dimensions within the MMs. The research articles studied have been taken from the period 2001-2019, keeping in mind the relevance of the articles in the evolving scenario of BI&A and technology as discussed by (Hsinchun Chen et al., 2012). The articles were analyzed using NVIVO 12 Plus, a tool for qualitative research and text analytics. This gave insights on the evolution of BI&A and the changing characteristics of data.

The review has used the digital libraries “EBSCO”, “EMERALD”, GOOGLE SCHOLAR” and other open sources using full text filter. A literature search was conducted using combination of keywords such as “analytics, business analytics, analytics adoption, business intelligence (BI), analytics implementation, analytics models, analytics maturity, analytics assessment, BI adoption, BI implementation, BI models, BI maturity, BI assessment, analytics capability, BI capability”.

The articles covered a range of areas like current state of BI&A, opportunities and challenges faced in Business Analytics in India, BI&A for functional areas like Operations, Financial Management, Human Resources, Supply Chain Management, BI&A for specific domains like Healthcare, emerging areas like web analytics, big data analytics and in-memory analytics.

There was a collection of research papers which mentioned maturity models, assessment of BI&A maturity in organizations and factors for adoption and implementation of BI&A. The maturity models for BI&A were examined from these papers. The dimensions found in all these maturity models were analyzed and an Expert Panel was consulted to consolidate the dimensions into a smaller number of critical factors which could assess BI&A capability maturity. Different maturity models had different maturity levels ranging from three to six levels. These were studied to understand how an organization could grow in maturity of BI&A capability from one level to the next.

This chapter has been organized as follows: The first section 2.2 describes BI&A, its importance, the evolution and conceptual foundation of BI&A, as stated by (Chen et al., 2012). An interesting inference drawn out by the researcher, about the changing and evolving characteristics of data, has been presented. This section also mentions requirements for implementation, the scope of BI&A in India, effectiveness of BI&A and building it as a capability in organizations.

The section 2.3 discusses the overview of maturity models (MMs), various MMs for BI&A, discusses understanding of maturity levels and how MMs are mapped to the conceptual foundation of BI&A. Section 2.4 discusses the study of dimensions within the MMs. Section 2.5 highlights the observations and research gaps found in the literature review and section 2.6 describes the operational definitions derived from literature review.

2.2 BUSINESS INTELLIGENCE & ANALYTICS - DEFINITION, EVOLUTION AND IMPLEMENTATION

Business Intelligence is a term used by researchers since 1950s and the term Business Analytics was introduced much later, in the late 2000s (Chen et al., 2012). In this study we have used the term Business Intelligence & Analytics as a unified term to denote the evolving nature of the capability.

In the early nineties, the term Business Intelligence (BI) was initially used as a standard name for describing methodologies and concepts for improving business decisions using data comprising of facts and information from various supporting systems by Howard Dresner (Power 2007). Business Intelligence and Business Analytics have been defined in many ways. Definitions differ depending on the authors and their perspectives. We have identified definitions which focus on the capability of the company to achieve advanced business goals and increase business efficiency:

- Business Intelligence is all about capturing data, accessing it, understanding the data, analysing and converting it. Data is one of the most invaluable and essential assets of the company, which is converted into active information in order to enhance business (Azvine et al. 2006).
- Business Intelligence is the capability of the organization to gather, understand, predict, manage problems and learn further to increase organizational proficiency in knowledge, provide information to the process of making decision, enable actions which are effective, and support and achieve business goals (Wells 2008).
- "The tools and techniques which are used for statistically and quantitatively analysing a large collection of data sources to add value and drive or support decision making in

business, are collectively known as Business Analytics. They have a focus in dealing with big data" (Aydiner et al., 2019).

BI&A technologies make it possible to collect data, analyse and deliver information. They are designed to support and enhance decision making (Rikhardsson and Yigitbasioglu, 2018). BI&A has been helpful to organizations in enhancing efficiencies to manage data and information required for making decisions. BI&A is more than just technology. It includes having a grasp on the association of many important organizational elements like people, process and technology areas within an organization. Many industries are very complex with complex laws and regulations, complicated stakeholder relationships and external market requirements. This makes it important to understand the industry domain with respect to issues or challenges with BI&A maturity as discussed by (Brooks et al., 2015). BI&A not only improves decision-making but the practise has been considered also for learning about organization and management, improving organization efficiency and intelligence. (Trieu, 2017).

2.2.1 Evolution of Business Intelligence and Analytics (BI&A)

(Hsinchun Chen et al., 2012) mention the conceptual foundation and evolution of Business Intelligence and Analytics from BI&A 1.0 to BI&A 2.0 and then to BI&A 3.0 and the characteristics associated with each phase. Key characteristics of BI&A 1.0 are, a structured database management system, ad-hoc reporting, data warehousing, ETL tools, Online Analytical Processing, dashboards, data mining and statistical analysis. The premise of BI&A 2.0 is social network analysis, social media analytics, information retrieval, web analytics and extraction of web based unstructured content. The key characteristics of BI&A 3.0 is mobile and sensor-based content, big data analytics, location aware and person centric analytics. These have been listed in Table 2.1.

Table 2.1 Conceptual foundation of BI&A

Evolution of BI&A	Key characteristics	No. of MMs found in literature	Maturity Models (MM)
BI&A 1.0	• Structured database management system • Ad-hoc reporting • Data warehousing, ETL tools • Online Analytical Processing (OLAP) Dashboards • Data mining and statistical analysis	13	• MM for Data Warehousing, • BI Readiness Assessment Model • SAS Information Evolution Model • AMR Research's BI/PM Model • TDWI DW Maturity Model • BiMM Steria Mummert Consulting • Enterprise Data Management MM • Ladder of Business Intelligence • Gartner's Maturity Model for BI & Performance Management • DELTA Model • Conceptual model of business value of business intelligence systems • HP Business Intelligence MM • Teradata's BI and DW Maturity Model
BI&A 2.0	• Web analytics • Social media analytics • Social network analysis • Information retrieval and extraction of web based unstructured content	12	• Business Intelligence Development Model • EBIM Model • Business Intelligence Maturity Hierarchy • Model of impact-oriented BI MM • Service-Oriented Business Intelligence Maturity Model • BI MM in Transitional Economies • Data Warehouse Process Maturity model • A Business Intelligence conceptual model • Capability Maturity Model for BI • BACMM • Enterprise Business Intelligence Maturity Model (EBI2M) • INFORMS Analytics MM
BI&A 3.0	• Mobile and sensor-based content • Big data analytics • Location aware and person centred analytics	4	• TDWI Big Data Analytics MM • BDMM – Big Data Maturity Model • Gartner's IT Score for Data & Analytics • APMM Framework

It has been observed that the conceptual foundation of the classification from BI&A 1.0 to BI&A 2.0 and further to BI&A 3.0, is the evolution in characteristics of data, source of data and the organizational capability to deal with this. Characteristics of data type, data accessibility, data context and sources from where data comes in are observed to have evolved.

Data type has evolved from being purely structured data to unstructured data. Most organizations deal with a variety of data ranging from numbers, text, image, video, clickstream, web and sensor data.

Data accessibility has increased manifold. Today due to the advances in technology and processing power, businesses have access to real-time data streaming in from the internet, mobile devices and sensor-based devices rather than only historical, offline data found in information system databases (Post and Edmiston, 2014), (Prakash, 2014).

The context of data has changed from being purely at an organizational level where data was used to analyse and understand patterns in sales, revenue and profit, to person centric data, with the ability to capture consumer profile, preferences, opinions, images, location and personal health data (Ranjit Bose, 2009).

Businesses today can capture data for consumers constantly on the move through their mobile device. Sources of data have evolved from data in organization servers and computers to data obtained from mobile devices which the current generation of consumers and businesses are quick at adopting (Jayaram et al., 2015).

The very nature of the evolution of the source of the data - from historical records (typically in the form or numbers) within an organisation to real time data (which maybe text, clickstream, image or video) from a mobile device makes it evident that data characteristics are rapidly evolving and changing. Apart from the type of data, a major change consequential to the tremendous increase in the sources of data, is the huge volume of data generated. This is commonly referred to as Big Data.

As mentioned by (Janssen et al., 2017), big data can offer some very different inflection areas for new insights and has the potential to improve decision-making. (Mashingaidze and Backhouse, 2017) in their paper, brought out the relationship between business intelligence, business analytics and big data, inferred that "Big Data is a type of data that is used in advanced Business Intelligence (BI). Business Analytics (BA) is a component of BI. Thus, big data can also be used as the data source for business analytics". As stated by (Gandomi and Haider, 2015), the real value of big data is unlocked only when it is leveraged to drive decision making. As per the study by (Ylijoki and Porras, 2018), managers today believe that, increased customer understanding, product and service enhancements and process streamlining are the most potential big data application areas.

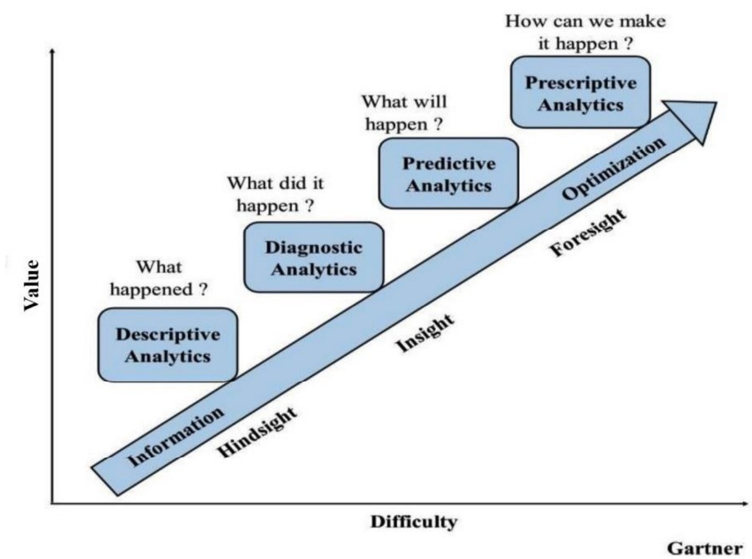

Figure 2.1 Evolution of the Analytics Continuum (Source: Gartner)

Another framework depicting the evolution of BI&A is the Analytics Continuum referred by Gartner Inc. This depicts the BI&A capability in an organization moving from descriptive to diagnostic to predictive and further to prescriptive. Preparing reports from data which are used to understand data summaries has been called 'descriptive' analytics, finding insights from data using various visualization tools is 'diagnostic analytics'. 'Predictive analytics' is used when predictive models are created using statistical tools to predict important business parameters like sales, growth, demand etc. The term ‘prescriptive analytics’ is used when actions are generated from results based on predictive models. These actions enhance the business value. This term has also been used for optimization and related techniques to the results of predictive models to enable actions which are based on the predictive outcomes (Grossman, 2018).

Clearly the context of BI&A capability is changing over time with evolving data characteristics and predictive and prescriptive requirements of organizations (Dobrev and Hart, 2015). Hence this study aims to help organizations to understand the factors influencing BI&A capability maturity, in the evolving scenario of BI&A with the emergence of big data and real time BI&A and its analytics.

2.2.2 Scope of BI&A in India

As per Gartner’s CIO 2019 agenda for BI&A in India, BI&A ranks as the topmost technology area attracting new or additional funding. Value creation in Indian businesses, is shifting to usage experience. India is moving from manufacturing and agrarian economy to “experience” economy, where business analytics and experimentation is the key to creating considerable competitive advantage (Murthy, 2006). . A study by (Xavier et al., 2011) suggests that senior managers in organizations in India are aware of BI&A and express familiarity with BI&A solutions.

The Telecom Services, BFSI (Banking, Financial Services and Insurance), ITES (Information Technology enabled services), Retail and FMCG (Fast Moving Consumer Goods) are the industry sectors where major chunk of analytics usage is seen (Banerjee et al., 2013). Analytics, big data and data science sector in India is currently estimated to be INR 17,615 crore annually (FY18) in revenues (Dataquest estimates), growing at a healthy rate of 33.5% CAGR. The annual inflow to the analytics industry is divided like this - almost 11% is attributed to advanced analytics, predictive modelling and data science, and a sizeable 22% may be attributed to big data. This industry in India is expected to grow seven times in the next seven years. The estimate is that it will become a INR 1,30,000 crore industry in India by 2025 as mentioned in (*DATAQUEST*, 2018).

Gartner 2019 survey for India revealed that Chief data officers (CDOs) along with their data and analytics (DA) teams had started emphasising on the right priorities, but they were not yet achieving an optimum balance of their various responsibilities in delivery of enhanced organizational performance. While they were focussing on some of the right things like creation of a data-driven culture, they did not have the right mix of the factors.

Therefore, this research attempts to help organizations in India identify the factors which influence their level of BI&A capability maturity, understand current maturity level and define a roadmap to move beyond the current maturity level of BI&A.

2.2.3 BI&A Implementation

Many organizations assume that the only prerequisite for a successful BI&A implementation is fast and accurate visually appealing reports. Contrary to this, there are various other aspects that must be taken into consideration in BI&A implementations, including organizational culture, business processes, people, the organizational environment, technology and resources. These additional elements can actually enhance or break down the BI&A implementation (PMP and RRT, 2012). Prior to any technology or system implementation, the organization needs to bring awareness about the technology's usefulness and ease of use, and promote organizational changes to refine communication and learning (Khan and Brock, 2017). The same applies for BI&A implementation in organizations.

Regular top management support through steering committees is very important for successful implementation of BI&A capability (Amrita Gangotra and Ravi Shankar, 2016). Encouraging an analytic culture from the top management starts with empowerment. A successful analytic culture must be free-flowing and top-down in a democratic way (Callahan, 2012). Fostering as opposed to implementing or forcing is key. This means that organizations have to empower and trust their workforce to explore and find insights from their own data (Mills, 2016).

As mentioned by (Popovič et al., 2012), a typical BI&A system implementation involves organizational, diverse technological and process issues, sharing close characteristics with other intelligence information system (IS) projects like enterprise resource planning (ERP) systems implementation. Since long, the information systems (IS) literature has stressed upon the positive effect of information generated by business intelligence systems (BIS) on decision-making, especially when organizations work in highly competitive environments.

Today many organizations emphasise on having BI&A for implementing solutions to improve their decision-making process. Yet, expectations have not been met in many BI&A initiatives. One of the main reasons for this is the lack of an understanding of the important factors that determine the success of BI&A applications and the understanding that BI&A capabilities are among one those critical factors (Isik et al., 2011). In spite of the emerging BI&A market and the complexities around the implementation of BI&A systems, the critical success factors (CSFs) of BI&A system implementation initiatives are still poorly understood. When the main factors that drive an organization's success are measured, monitored and predicted, that organization is found to be more agile to adjust, advance, and mitigate risks. That is, if a company is able to realise and not just guess which nonfinancial performance attributes directly influence financial output, then it has an upper hand on its competition and can deliver real value to its employees, shareholders, and other stakeholders (Maisel and Cokins, 2014).

This study attempts to identify the critical factors required for building BI&A capability to make BI&A implementations successful in organizations in India.

2.2.4 Effectiveness of BI&A for Organizations

Evaluating the effectiveness of BI&A is vital to an organization's understanding of the value of management actions and investments. To achieve maximum enterprise value, BI&A projects should be approached as partnerships between Business and IT (Viaene and Den Bunder, 2011).

Leaders of companies are increasingly investing in analytics as a means of enhancing business performance (Anthony Marshall et al., 2015). New positions at the board table, such as a CAO - Chief Analytics Officer are being developed and the analytics team is getting upgraded to learn new skills to meet the new challenges (Lismont et al., 2017). Accenture Research shows that high-performing businesses have a highly developed analytical orientation than other organizations. They are five times more likely than their competition to regard analytical capabilities as being core to the business.

Conducting a BI&A readiness assessment in an organization can be helpful in understanding the culture and readiness level for BI&A technologies and strategies. A BI&A readiness assessment goes further than an analysis of the technology infrastructure. It must also expand to an understanding of policy, culture, governance and business processes. One approach for assessment of business intelligence readiness is by using a maturity model, and more specifically, a business intelligence maturity model.

There is a lot of research about BI&A investments, BI&A assets, BI&A impact for improved organizational performance. But there is not enough research on processes or conditions required to link these together (Trieu, 2017). Hence research is unable to provide a complete view of how business value is generated from BI&A. As per a study conducted by (Fink et al., 2017), there is a dual approach to BI&A value creation, that of operational value and of strategic value and for both of these, BI&A capabilities play a pivotal role.

There is a gap in understanding exactly how and where is the effectiveness of BI&A seen in organizations. This research aims at fulfilling this gap by understanding the effectiveness of BI&A in organizations in India.

2.2.5 Building BI&A as a capability in organizations

The ability to generate insights from data and use them for decision making has become an essential capability for organizations today as mentioned in a special issue of MIS Quarterly on transformational matters on Big Data & Analytics in networked business (Baesens et al., 2016). This can be achieved by improving the capability of BI&A.

The study by (Trieu, 2017) suggests that operational and strategic BI&A capability evolve independently and are to be considered separately. They define strategic BI&A capabilities as "repetitive actions of using BI&A assets to aid strategic organizational activities, like assessing organizational performance; recognizing trends, opportunities, and threats in the business environment; and establishing new corporate strategies". Similarly, they define operational BI capabilities as "repetitive actions of using BI assets to support operational organizational activities, such as integrating different types of data analysis in transactional activities; modelling and optimizing production and service processes; and sharing relevant data across business unit". This study establishes a relationship between BI&A assets which include physical and human assets, BI&A capabilities and BI&A value, both operational and strategic.

As per (Božič and Dimovski, 2019a), all levels of management need to be aware of the BI&A capability to provide more holistic and accurate business intelligence, which requires a continuous effort from the organizational front. The recent study by (Moreno et al., 2019) has confirmed that support from Information Technology and organizational resources and capabilities complement each other in generation of business value from BI&A capability.

Also in the era of big data, (Wamba et al., 2017) suggests that to convert big data analytics capability into organization performance, managers have to focus on technology and infrastructure capability. In a study by (Krishnamoorthi and Mathew, 2018), they attempt to discover how BI&A contributes to business value in organizations. Their model also proposes a focus on Business Analytics capability.

We may conclude that measuring and building BI&A capability seems to be important to create value through BI&A. And maturity models are the tools that will facilitate the measurement or assessment of how well developed are the organizational capabilities, processes and resources (Cosic et al., 2012). Therefore, in this study, maturity models for BI&A were examined to understand the factors which help in assessing BI&A capability maturity.

2.3 MATURITY MODELS FOR BUSINESS INTELLIGENCE AND ANALYTICS CAPABILITY

Maturity models explain and evaluate the growth life cycle of a capability. The concept of a maturity model (MM) was studied. An overview is given in this section. In particular, BI&A maturity models, their maturity levels and dimensions were studied. This fulfilled the first objective of this research.

2.3.1 Overview of Maturity Models

Maturity models (MMs) are used to explain and measure growth life cycles. The entire basis of the maturity models is that things change longitudinally over time and these changes can be foreseen and managed. Different domains and practices have different models. Many authors build and improve their models based on the earlier experience of other authors (Hribar Rajterič, 2010).

A MM typically consists of a sequence of maturity levels for a class of objects or dimensions (Becker et al., 2009). At each level, the dimensions on that level have to achieve certain requirements. Maturity here is understood as measure to evaluate the organizational capabilities while the term capability stands for the ability to achieve a predefined goal (Raber et al., 2013). The various stages of a model are defined and identified by a set of characteristics or dimensions which have their own maturity cycles. To progress from a lower stage of maturity to a higher stage requires changes in all of the dimensions that make up the stages. While all of the stages of the dimensions do not have to be exactly at the same level, they should be more or less at the same stage of evolution (Denbu Wilhelmsson and Eriksson, 2013).

Maturity models have various purposes which include descriptive, prescriptive and comparative (De Bruin et al., 2005). A descriptive maturity model is used to measure the as-is maturity condition in an organization (Maier et al. 2009). A prescriptive model additionally includes guidelines for enhancing maturity at each level, and enables organizations to identify future levels of maturity which may be desired by the organization (Becker et al. 2009). A comparative maturity model is essentially used for comparison. It is a prescriptive model that has been used in a large number of organizations and hence that historical data can be used for comparative purposes (De Bruin et al., 2005).

It is a usual norm to measure the maturity of any capability along five possible levels of maturity, from initial adhoc, when the organization is beginning to realize the existence and potential of a capability, to optimizing, when a capability is widespread in the organization, effectively managed and regularly reviewed for improvement (Comuzzi and Patel, 2016).

Maturity models have been developed to measure the maturity (capability, competency, sophistication level) of a selected practice or domain based on a comprehensive set of criteria (De Bruin et al., 2005). The five-point Likert scale with '5' representing the highest level of maturity is one of the most standard and popular method of assessing maturity. There are a large number of maturity models which have emerged across domains since the concept of measuring maturity was introduced with the Capability Maturity Model (CMM) from the Software Engineering Institute (SEI) – Carnegie Mellon. The SEI had created six maturity models in total, incorporating three legacy CMMs into one maturity model named the Capability Maturity Model Integration – CMMI (Ahern et al. 2004). Two other stand-alone models include the People Capability Maturity Model and the Software Acquisition Capability Maturity Model. However, the SEI is not the only developer of methods to assess maturity.

More than 150 maturity models have been developed to measure the maturity of Strategic Alignment, IT Service Capability, Program Management, Knowledge Management, Enterprise Architecture and Innovation Management Maturity. Most of these models simply provide a means for finding the position of the chosen unit of analysis on a pre-defined scale, unlike CMM which has reached the level of a compliance standard (Mutafelija and Stromberg 2003).

The concept of information maturity is the key to understanding results of any measurement being performed. Ladley has mentioned capability as one of the important areas to evaluate Information Management Maturity (IMM). In the IMM Model he states there are five levels to mature in – initial, repeatable, defined, managed and optimized. There is no good or bad level of maturity, maturity is not a score; every organization has an appropriate level of maturity which works well for their business model. An organization may be at their appropriate level or many levels away from that (Ladley, 2010).

2.3.2 BI&A Maturity Models

As BI&A is a vast area, valuable and good quality maturity models covering both technological and non-technological aspects are not seen to develop quickly. One more challenge is that BI&A is one of the most rapidly growing and developing areas, having a number of guidelines for development. The key factor in upgrading business value in the BI&A area is realizing that the maturity level of the capability within the company must match the maturity level of the company itself as far as possible. Only then the benefit of BI&A will be highest (Hribar Rajterič, 2010). This holds true about BI&A in organizations today as well. Although the concept of BI&A has been established since more than a decade, it is fairly new and there is not enough study to provide structured maturity guidelines and readiness assessment. This shortcoming arises from the fact that, the BI&A market is a relatively new practice, with most of the pioneering work being driven by various IT vendors in the market.

BI&A maturity models illustrate how BI&A has emerged from being low-value, cost-centric operations to high-value, strategic utilities that drive market share (TDWI, 2005). In the current business scenario, there are ample number of BI&A maturity models (TDWI, 2005; Williams and Williams, 2010). They provide organizations an 'instant perspective' on the current status of their BI&A initiative as explained by (Popovic et al., 2010). The impact of BI&A demands for a structured, transparent, and comprehensive measurement and analysis of existing BI&A solutions in organizations. BI&A-specific maturity models can contribute well in this context.

A maturity model can be used as a readiness assessment and measurement tool for developing a BI&A strategy. A maturity model assumes that progress comes in stages, finally reaching a goal in the end (Chuah & Wong, 2011). A maturity model may mature with its continuous application leading to revisions and refinement of the model (Popovic et al., 2010).

(Lahrmann, 2011) argues that maturity is a state of being "complete, perfect or ready". It has to present causes, (e.g. "BI technology deployed"), as well as effects, (e.g. "organizational impact of BI realized"). MMs need to focus on both cause and effect as MMs focusing only on effects may not give insights on how to improve the current situation. Therefore, they are of limited practical utility. Also MMs focusing only on causes may not give insights on the value found, thereby making it incomplete.

There has been large amount of engagement over years with maturity models where it is concluded that maturity models can never be truly without bias (Dinter, 2012). A maturity model will always have some amount of ambiguity and subjectivity even of it is developed with help of empirical analysis, e.g when identifying the overall maturity level using the dimensions and their characteristics, there will always be some amount of subjectivity involved, especially if there are large number of dimensions.

Building on this argument and to remove all bias, this research looks at all the dimensions across different BI&A MMs to find the critical success factors which influence the maturity of BI&A capability rather than focusing on only one of the MMs.

In order to document existing BI&A MMs and identify their key characteristics, Table 2.2 shows chronological list and overview of MMs, including their dimensions and maturity levels. The study identified 29 maturity models (MM) for BI&A. While there was a lot of research on Business Intelligence before the 2000s, a maturity model for BI&A was found to be created only in 2001. The BI&A MMs given in Table 2.2 range from 2001 to 2018. A standard model which has been largely used by academicians and practitioners as a basis for the BI&A MMs is Paulk et al.'s (1993) Capability Maturity Model (CMM) for software development. There was no standard MM found for BI&A which was as popular and accepted as the CMM.

Table 2.2 Overview of Maturity Models (2001-2018)

S.No	Name of the Model	Author & Year	Description	Dimensions	Maturity Levels
1	MM for data warehousing (DW)	Watson et al. (2001)	Based on concept of stages of growth, where theory says that change happens across time progressively and predictably.	Data, architecture, stability of production environment, DW staff, DW users, impact on users skills and jobs, use of DW, applications, organizational impacts, costs & benefits	• Initiation • Growth • Maturity
2	BI Readiness Assessment Model	Williams et al. (2004)	Focus is on improving BI importance with vision and cultural changes in use of information and assesses BI readiness in an organization from the business perspective	BI strategic alignment, Partnership between business units and IT, Continuous process improvement culture, BI portfolio management, Information and analysis usage culture, Decision Process Engineering culture, BI & DW Technical readiness	
3	SAS Information Evolution Model Hatcher et al.	SAS (2004)	Aids organizations in assessment of how information is managed as a corporate asset and used to drive business. Reliability for this is unclear as theory and process have not been addressed.	People, Process, Culture, Infrastructure	• Level 1 – Operate • Level 2 – Consolidate • Level 3 – Integrate • Level 4 – Optimize • Level 5 – Innovate
4	AMR Research's	AMR Research (2004)	Used to measure the areas of Business	-	• Reacting (where have we been?)

S.No	Name of the Model	Author & Year	Description	Dimensions	Maturity Levels
	Business Intelligence/ Performance Management		Intelligence and Performance Management in an organization		• Anticipating (where are we now?) • Collaborating (where are we going?) • Orchestrating (are we all on the same page?)
5	TDWI DW Maturity Model	Eckerson (2004)	This framework helps organizations gauge their past, current and future position for analytics deployment.	Organization, Infrastructure, Data management, Analytics Governance	• Prenatal • Infant • Child • Teenager • Adult • Sage
6	SMC BiMM Steria Mummert Consulting (SMC)	Chamoni et al. (2004)	This model has been developed using iterative design research process. It is used to measure business, system and organizational aspects of BI.	Functionality-scope, data architecture, penetration level; Technology-technical architecture, data management, information design; Organization - structure, processes, profitability, strategy	• Level 1 – Single report view • Level 2 – Department led business understanding • Level 3 – Focusing • Level 4 – Strategic alignment • Level 5 – Operational understanding
7	Enterprise Data Management MM	DataFlux (2005)	Maturity measurement is based on organizational capabilities. Cost-benefit analysis of moving to next level is considered here. Focus on data management.	People, Process, Technology Risk & Reward	• Unaware • Reactive • Proactive • Predictive
8	Ladder of Business Intelligence (LOBI)	Cates et al. (2005)	Focus here is effectiveness and efficiency of decision making. Not well documented model	Information Technology, Processes, People	• Facts • Data • Information • Knowledge • Understanding/Perception • Enabled Intuition
9	Gartner's Maturity Model for Business Intelligence and Performance Management (BI & PM)	Gartner Inc. (2006)	Assessment of BI and PM and mature they need to be to reach the business goals.	People, Processes, Metrics and Technology	• Unaware • Tactical • Focused • Strategic • Pervasive

S.No	Name of the Model	Author & Year	Description	Dimensions	Maturity Levels
10	DELTA model	Davenport et al. (2007)	Focus is on capabilities and assets needed in an organization to succeed in the analytical initiatives.	Data, Enterprise, Leadership, Targets, Analysts	• Analytically impaired • Localized analytics • Analytical aspirations • Analytical companies • Analytical competitors
11	Conceptual model of business value of business intelligence systems Based on the maturity model by Williams et al. (2004)	Popovic et al. (2010)	Focus is from the IT viewpoint – measuring data sources within the organization, level of data integration, and different analytics usage.	Strategy alignment, Culture of continuous process improvement, Culture of information use and analysis, Decision process management, Cooperation between IT, Business technological readiness	• Stage 0 • Stage 1 • Stage 2 • Stage 3
12	HP BIMM	Hewlett Packard (2009)	Focus on three organizational capabilities. This was created by HP to understand client BI maturity levels.	Business enablement, Information Technology Strategy, Program Management	• Operations: organizations focus on running the business. • Improvement: organizations focus on measuring and monitoring the business • Alignment: in which organizations are focused on integrating performance management and intelligence • Empowerment: in which organizations are focused on business innovation and people productivity • Excellence: in which organizations are focused on strategic agility and differentiation
13	Teradata's BI and DW MM	Topfer J. (2008)	Focus is on impact of BI on business processes.	No documentation found in research papers	• Reporting (what happened?) • Analyzing (why did it happen?) • Predicting (what will happen?) • Operationalizing (what is happening?) • Activating (make it happen)
14	Business Intelligence	Sacu et al. (2010)	Focus is to identify current stage and	People, Process, Technology	• Predefined reporting

S.No	Name of the Model	Author & Year	Description	Dimensions	Maturity Levels
	Development Model (BIDM)		reach the desired one.		• Data marts • Enterprise-wide DW • Predictive analytics • Operational BI • Business performance management
15	EBIM Model	Tan et al. (2011)	Proposed to manage a business intelligence initiative	Information Quality (IQ), Master Data Management (MDM), Warehousing Architecture, Analytics	No documentation found in research papers
16	Business Intelligence Maturity Hierarchy	R.Deng (2011)	The basis of this model is Knowledge management	No documentation found in research papers	• Stage 1: Data • Stage 2: Information • Stage 3: Knowledge • Stage 4: Wisdom
17	Model of impact-oriented BI MM	Lahrmann et al. (2011)	Theoretical model based on BI impact and combining IS theories and BI MM research.	Deployment, Use of BI – Individual and Organization, Impact of BI – Individual and Organization	No documentation found in research papers
18	Service-Oriented Business Intelligence Maturity Model (SOBIMM)	Shaaban et al. (2011)	Model created on the basis of Service Oriented BI to solve problems around information integration and poor planning.	Technology, Organization, Business proficiency	• Initial • Immature • Controlled • Managed • Mature
19	BI Maturity Model in Transitional Economies context	Lukman (2011)	Model created with empirical study on Slovenian organizations that covers the entire breath of BI and overcomes weakness of existing models which focus on technical aspects.	Technology, Information Quality, Business Perspectives	Clusters were identified in increasing level of maturity • Cluster 1 • Cluster 2 • Cluster 3 • Cluster 4
20	Data Warehouse Process Maturity model (DWP-M)	Sen et al. (2011)	Model based on the CMM levels. Focus on data change management, data governance, data quality assurance.	Large number of dimensions based on DW development and DW operations	• Level 1: Initial • Level 2: Repeatable • Level 3: Defined • Level 4: Managed • Level 5: Optimized

S.No	Name of the Model	Author & Year	Description	Dimensions	Maturity Levels
21	Business Intelligence Conceptual Model BISCOM	Glancy et al. (2011)	Process focused for developing, evaluating and understanding BI.	No documentation found in research papers	No documentation found in research papers
22	Capability Maturity Model for BI	Raber D. (2012)	Based on Lahrmann's model. Developed using cluster analysis and quantitative analysis.	Strategy, Social system (Organization), Technical system (IT), Quality of service, Use/Impact	• Level 1: Initiate • Level 2: Harmonize • Level 3: Integrate • Level 4: Optimize • Level 5: Perpetuate
23	BACMM	Cosic et al. (2012)	Developed as a model based in theory and context, with a holistic view of Business Analytics for for-profit Australian organizations	Technology, People, Culture Governance	• Level 0: Non Existent • Level 1: Initial • Level 2: Intermediate • Level 3: Advanced • Level 4: Optimized
24	Enterprise Business Intelligence Maturity Model EBI2M (2012)	Chuah et al. (2015)	Fairly new model and not well documented. Focus on enterprise level tools, techniques and business changes.	Change management, Organizational culture, Strategic management People, Infrastructure, Knowledge management, Data warehousing, Information Quality, Master data management, Metadata management, Analytical performance management, Balanced scorecard	• Initial • Managed • Defined • Quantitatively managed • Optimizing
25	INFORMS Analytics MM	List et al. (2014)	Used for organizations that are not yet into BI&A function as well as, those that are aiming for higher levels of BI&A maturity.	Organizational practices and culture: People, Leadership Impact, Measures & Processes; Analytics capability: Roles & skills, analytics governance, services, processes; Data & Infrastructure: Health, access, traceability and architecture	• Beginning • Developing • Advanced
26	TDWI Big Data	Halper et al. (2013-14)	Focus is on Big data and how it may be used to	Organization, Infrastructure, Data	• Nascent • Pre-adoption • Early Adoption

S.No	Name of the Model	Author & Year	Description	Dimensions	Maturity Levels
	Analytics MM		derive value to business.	management, Analytics, Governance	• Corporate Adoption • Mature / Visionary
27	BDMM – Big Data Maturity Model	Comuzzi et al. (2016)	This model integrates all industry developed MM to make one which focus on Big Data and its implications for business.	Strategic Alignment, Data Organization, Governance, Information Technology	• Level 0 • Level 1 • Level 2 • Level 3 • Level 4 • Level 5
28	Gartner's IT Score for Data & Analytics	White et al. (2017)	Focus is on assessment of shortcomings, priorities and actions for improving the maturity and performance of analytical programs.	Data & Analytics, Vision & Strategy, Value & Outcome management, People, Skills & Organization, Technology & Solutions Implementation	• Basic • Opportunistic • Systematic • Differentiating • Transformational
29	APMM Framework	Robert L Grossman (2018)	Focus on evaluating the BI&A maturity of an organization based on the extensive dimensions identified.	Analytical model building, Deploying analytic models, Analytic infrastructure, Analytic governance structure, Security and compliance for analytical assets, Developing analytical strategy	• Build reports • Build models • Repeatable Analytics • Enterprise Analytics • Strategy driven analytics

Watson's MM was one of the earliest maturity model which included three levels and had dimensions of people, process and technology. A prescriptive model of five levels was defined by Davenport and Harris (2007). There are MMs which have been developed by vendors and consulting companies (for e.g.: Teradata, SAS, TDWI and Gartner) based on their consulting experience. These models lacked a theoretical foundation Lahrmann's model was grounded in theory – it was a prescriptive BA maturity model. The focus in this model is on the impact of BI capabilities rather than on capabilities itself. In general, it was found that BI&A maturity models lack grounding in theory and focus too much on the data warehousing aspect of BI&A (Cosic et al., 2012) rather than on the emerging big data environment for business.

To take a historical view of the MMs, some have an origin in academics and some in practice, as seen in Table 2.3. Different exploratory research methods and combinations of these methods were found to be proposed for developing MM. The commonly found methods are Literature Analysis, Case Study Method, Delphi and Focus Group Discussions (Becker et al., 2009). The various methods used in developing the BI&A MMs can be seen in Table 2.3.

Table 2.3 Maturity Model Origin & Method of Development

S.No	Name of the Model	Year	Topic	Origin	Method of model development
1	MM for data warehousing (DW)	2001	DW	Academic	Interviews with industry experts (Qualitative)
2	BI Readiness Assessment Model	2004	BI	Practice	Case study method (Qualitative)
3	SAS Information Evolution Model	2004	Information Management	Practice	Unclear
4	AMR Research's Business Intelligence/Performance Management	2004	BI/PM	Practice	Unclear
5	TDWI DW Maturity Model	2004	DW	Practice	Literature analysis
6	SMC BiMM	2004	BI	Academic	Focus groups & survey
7	Enterprise Data Management MM	2005	Data Management	Practice	Unclear
8	Ladder of Business Intelligence (LOBI)	2005	BI	Academic	Case study method
9	Gartner's Maturity Model for Business Intelligence and Performance Management	2006	BI & PM	Practice	Case study method
10	DELTA model	2007	Analytics	Academic	Case study method
11	Conceptual model of business value of business intelligence systems	2008	Business Value of BI	Academic	Case study method
12	Teradata's BI and DW MM (2008)	2008	BI & DW	Practice	Case study method based on clients experiences
13	HP BIMM	2009	BI	Practice	Case study method based on clients experiences
14	Business Intelligence Development Model (BIDM)	2010	BI	Academic	Literature survey & analysis
15	EBIM Model by Tan, Sim, &Yeoh	2011	BI	Academic	Structured questionnaire survey
16	Business Intelligence Maturity Hierarchy	2011	BI	Academic	Unclear

S.No	Name of the Model	Year	Topic	Origin	Method of model development
17	Model of impact-oriented BI MM	2011	BI	Academic	Theoretical development through literature analysis
18	Service-Oriented Business Intelligence Maturity Model (SOBIMM)	2011	BI	Academic	Theoretical development through literature analysis
19	BI Maturity Model in Transitional Economies context	2011	BI	Academic	K-means clustering,
20	Data Warehouse Process Maturity model (DWP-M)	2011	DW	Academic	Field study and survey through questionnaire
21	BISCOM	2011	BI	Academic	Design Theory
22	Capability Maturity Model for BI	2012	BI	Academic	Item Response Theory based approach with Cluster Analysis
23	BACMM	2012	Business Analytics	Academic	Design Science research approach
24	Enterprise Business Intelligence Maturity Model EBI2M	2012	BI	Academic	Delphi Study Approach
25	INFORMS Analytics MM 1	2012	Analytics	Practice	Unclear
26	TDWI Big Data Analytics MM	2014	Big Data analytics	Practice	Case study method
27	BDMM – Big Data Maturity Model	2016	Big Data Analytics	Academic	Literature review and in-depth interviews & case study
28	Gartner's ITScore for Data & Analytics	2017	Data & Analytics	Practice	Case study method
29	APMM Framework	2018	Analytics	Academic	Unclear

Based on Table 2.3 and the understanding of the different methods of development of the models, the methods used in this study are Literature review and analysis, questionnaire design and administration, case study method and interviews.

While there are a large number of maturity models for BI&A, there are very few which consider the current evolving scenario of Big Data and Analytics around it. There is also no empirical study done with organizations in India to assess the BI&A capability maturity.

2.3.3 Maturity levels in BI&A Maturity models

Maturity can be defined as measurement of an organization's ability for continuous improvement in order to reach a state of being ready with an ecosystem which can reap intended benefits (Davenport and Harris, 2007). Similarly, a BI&A maturity model can help in charting out an evolutionary transformation path from the existing stage to the target stage and help an organization to closely align with its business practices and strategic objectives as stated by (Davenport et al., 2010). Organizations should be deriving more value from their investments as they move through these stages. (Halper and Krishnan, 2014).

A maturity model consists of stages of maturity levels for a set of elements and represents a desired or typical evolution path of these elements (Becker et al., 2009), starting at an early stage up to full maturity. At each level, the maturity assessment is based on the dimensions which have been defined in the model which the organization must focus on (White and Oestreich, 2017). However, higher maturity levels may or may not represent a desired target state. This will be decided individually by each organization (Dinter 2012).

The stages or levels of a maturity model are defined by a number of characteristics including scope, analytic structure, manager's perception, types of analytics, stewardship, funding, technology platforms, change management, data management and data administration. Organizations evolve differently through these stages and each one may display characteristics of multiple stages at a given time (Eckerson, 2004).

From the 29 maturity models found in literature review, most of them were found to have between three to five maturity levels. Three of them had six levels of maturity. The maturity levels have been given meaningful names in different models which depict the level of BI&A maturity. These have been clearly listed for each model in Table 2.2.

2.3.4 Mapping BI&A Maturity Models to the evolution period of BI&A

Through a systematic study of the maturity models (MMs), from the 29 MMs found in literature as well as a text search query made using NVIVO 12 Plus, on the papers which referred to the 29 BI&A MMs, only 4 of these MMs were found to refer to Big Data Analytics in the BI&A 3.0 evolution phase, 12 MMs were found to be from BI&A 2.0 and 13 MMs from BI&A 1.0. The text search query was made on "big data", "unstructured data", "web analytics" and "social media analytics". It was observed that the MMs that referred to these concepts were all created after 2011.

In recent years, managers perceive big data as an instrument to add value, for example, to develop upgraded efficient processes, add value to existing products or services, and increase understanding of the customer (Ylijoki and Porras, 2018). Yet, there were only 4 out of 29, developed from year 2013-2018 - three models and one framework which referred to the evolution of BI&A and big data in particular. The three MMs are TDWI's Big Data Analytics Model (Halper and Krishnan, 2014), BDMM – Big Data Maturity Model (Comuzzi and Patel, 2016) and Gartner's ITScore for Data & Analytics (2017) and the framework is Grossman's APMM framework (2018). It is observed that, in general, BI&A maturity models lack grounding in theory and focus on the technical aspects of BI&A like data warehousing (Cosic et al., 2012) rather than on organization capabilities for the emerging big data environment for business.

It was observed that most of the MMs were not based on the evolving nature of data hence they were not relevant for industry today. Therefore, understanding of all the dimensions from the MMs was necessary to derive relevant and consolidated set of factors for organizations in the current times.

2.4 STUDY OF THE DIMENSIONS IN THE BI&A MATURITY MODELS

Dimensions may be defined as specific capabilities which describe various aspects of the maturity. Every maturity model has multiple dimensions. Dimensions maybe disjoint, exhaustive and well defined. Each dimension can be further described by characteristics or measurement items. These could be practices, measures or activities (Raber, 2012).

Based on Lahrmann's comprehensive work on existing maturity models, he says results show that classic IT topics, e.g. data, applications and infrastructure, are highly present, while other topics like staff, strategy, efficiency and organizational structures, are very rarely addressed. Even though BI organization (e.g. BI competency centres) and BI strategy (e.g. strategic alignment) are two topics highly found present in IS literature, organizational structure and strategy are rarely addressed in the earlier maturity models. With respect to people, users and staff are separately identified. While five models talk about users, only one model explicitly mentions staff. Large number of earlier models refer to dimensions of people, process and technology. Only the later models refer to culture, governance and alignment with business strategy.

Each of the 29 maturity models as mentioned in Table 2.2, had multiple dimensions. In total there were 108 dimensions from 29 MMs, obtained from the literature review. These have been shown in Table 2.4 along with their maturity model and their description as found in literature review.

Table 2.4 List of 108 dimensions found from literature review

S.No	Dimension /Factor	Model/Author	Description as found in Literature
1.	Data	MM for data warehousing (DW) Watson et al. (2001)	Number of subject areas, data models used and quantity of data stored
2.	Architecture		The structure of marts and data warehouses
3.	Stability of production environment		Established processes for maintaining and expanding the warehouse (ETL)
4.	People - staff		Persons managing the data warehouse
5.	People- users		Persons using the data warehouse
6.	Impact on skills & jobs		How users jobs and required skills change because of DW
7.	Applications		Kinds of applications that utilize warehouse data
8.	Organization impact		How much impact the warehouse has on organizational performance
9.	Costs & benefits		Costs & Benefits associated with the DW
10.	BI strategic alignment	Business Information Maturity Model. Williams et al. (2004)	Consistency between business strategy, business organization and processes, IT strategy, IT infrastructure, and IT organization and processes

S.No	Dimension /Factor	Model/Author	Description as found in Literature
11.	Partnership between business units and IT		Using BI to create business value requires an effective partnership between business and IT, with continuous business involvement being essential
12.	Continuous process improvement culture		Organizations that have embraced continuous process improvement
13.	BI Portfolio Management		A wide range of BI applications can improve the performance of the functional units within a given company, including applications that help drive revenue growth and those that help optimize costs and profits. Companies that have undertaken a comprehensive review of the major BI opportunities for sales, marketing, manufacturing, distribution, customer service, quality, and so forth are in the position to manage BI as a portfolio of investments, ranked by business impact and risk
14.	Information and analysis usage culture		Organizations accustomed to using information, analytical frameworks, and quantitative analysis
15.	Decision Process Engineering culture		Organizations that have experience with structured decision process are more adept at rolling out BI applications that can create business value
16.	BI & DW Technical readiness		Effective technical execution of DW/BI initiatives requires proven methods for managing, designing, developing, and deploying BI that creates value
17.	People	SAS Information Evolution Model Hatcher et al. (2004)	Who is involved in the use of information?
18.	Process		What information related activities are to be performed?
19.	Culture		How do things get done in the information environment?
20.	Infrastructure		What information related technologies, tools, policies and governance need to be in place?
21.	Organization	TDWI BI MM Eckerson (2004)	To what extent do the organizational strategy, culture, leadership, skills, and funding support a successful analytics program? Additionally, is the company organized for success in analytics? Are analytics widespread and used in everyday decisions
22.	Data Management		How extensive are the variety, volume, and velocity of data used in analytics, and how does the company manage its data in support of analytics
23.	Infrastructure		How advanced and coherent is the architecture in support of an analytics initiative? To what extent does the infrastructure support analytics for all parts of the company and potential users?

S.No	Dimension /Factor	Model/Author	Description as found in Literature
			What technologies are in place to support an analytics initiative and how are they integrated into the existing environment
24.	Analytics		How advanced is the company in its use of analytics? How analytics contributes to decisions made throughout the company?
25.	Governance		How coherent is the company's data governance strategy in support of its analytics program? Is the company able to manage users' data discovery and analytical explorations effectively without applying too many restrictions and getting in the way of their pursuit of insight?
26.	Functionality Scope, data architecture, penetration level	BiMM Chamoni et al.(2004)	Not explicitly documented
27.	Technology – technical architecture, data management, information		Not explicitly documented
28.	Organization - structure, processes, profitability, strategy		Not explicitly documented
29.	People	Enterprise Data Management MM Dataflux (2005)	Documentation not found
30.	Process		Documentation not found
31.	Technology		Documentation not found
32.	Risk & reward		Documentation not found
33.	Information Technology	Ladder of Business Intelligence (LOBI) Cates et al (2005)	Not explicitly documented
34.	Processes		Not explicitly documented
35.	People		Not explicitly documented
36.	People	Gartner's Maturity Model for BI & PM Gartner Inc.(2006)	Business Driven and Collaboration
37.	Process		Not explicitly documented
38.	Metrics and Technology		Data, BI and analytics tools and technology
39.	Data	DELTA model Davenport et al. (2007)	Accessible high quality data
40.	Enterprise		Enterprise orientation
41.	Leadership		Analytical Leadership
42.	Targets		Strategic targets
43.	Analysts		Skills required for analysts
44.	Business enablement	HP BIMM Hewlett Packard (2009)	describes the advancing nature of the types of business needs and problems that are solved with BI solutions
45.	Information Technology		describes the advancing nature of the information solutions a company adopts to serve a variety of business needs
46.	Strategy & program management		describes the advancing nature of management skill as a key enabler and catalyst for BI success

S.No	Dimension /Factor	Model/Author	Description as found in Literature
47.	People	Business Intelligence Development Model (BIDM) Sacu et al. (2010)	Documentation not available
48.	Process		Documentation not available
49.	Technology		Documentation not available
50.	Information Quality (IQ)	EBIM Model Tan et al. (2011)	How information quality is managed and the processes for the same treated?
51.	Master Data Management (MDM)		How is the master data managed?
52.	Warehousing Architecture		What is the data architecture?
53.	Analytics		What is the analytical culture of the organization
54.	Deployment	Model of impact-oriented BI MM Lahrmann et al (2011)	Capabilities, practices, BI IT and organizational support from the deployment system
55.	Use of BI		Use of BI can be differentiated into individual use or organizational use
56.	Impact of BI		Impact of BI maybe on individual or organization
57.	Technology	Service-Oriented Business Intelligence Maturity Model (SOBIMM) Shaaban et al. (2011)	This is a combination of data and infrastructure
58.	Organization		Not explicitly documented
59.	Business Proficiency		Not explicitly documented
60.	Technology	BI Maturity Model in Transitional Economies context Lukeman (2011)	Technological components - s/w tools and applications and processes that together enable the production of useful information
61.	Information Quality		IQ relates to quality of information content and to quality of access of information
62.	Business Perspectives		What organization is doing with the information from BI and how is differentiation achieved. Main areas of BI use are 1- Within business process management 2- Within decision making activities - managerial processes
63.	Strategy	Capability Maturity Model for BI Raber et al. (2012)	These dimensions have been arrived at from the analysis of causes of Information systems success -the BI capabilities of the organizations. IS can be understood as a combination of “strategy” and “infrastructure and processes”, which can be further divided into “social system” and “technical system”
64.	Social system (organization)		
65.	Technical system (IT)		
66.	Quality of service		
67.	Use/Impact		
68.	Technology	BACMM R. Cosic (2012)	Development and use of hardware, software and data within Business analytics (BA) activities
69.	People		All those individuals within an organization who use BA as part of their job function.

S.No	Dimension /Factor	Model/Author	Description as found in Literature
70.	Culture		The tacit and explicit organizational norms, values and behavioral patterns that form over time and lead to systematic use of gathering, analyzing and disseminating data
71.	Governance		The mechanism for managing the use of BA resources within an organization and the assignment of decision rights and accountabilities to align business analytics initiatives with organizational objectives
72.	Change management	Enterprise Business Intelligence Maturity Model EBI2M Chuah et al. (2012)	Involves organizational change processes, including business process changes induced by IT investments in enterprise
73.	Organizational culture		The way people think can influence on the ways in which they behave
74.	Strategic Management		Activities that organization must do in order to improve business performance
75.	People		Illustrated that the quantifiable aspects to evaluate the company's human capital is their capabilities, recruitment, training and assessment.
76.	Knowledge Management		Method that assists the organizations to identify, select, organize, distribute, and transfer an essential information and expertise
77.	Information Quality		"Fitness for use", which means that the information with quality considered suitable for one use may not suitable for another use
78.	Data warehousing		Contains historical and current data that were organized and summarize, so end users could easily view or manipulate data and information.
79.	Master Data Management		A collection of best data management practices that orchestrate key stakeholders, participants, and business clients in incorporating the business applications, information management methods, and data management tools to implement the policies, procedures, services and infrastructure to support the capture, integration, and subsequent shared use of accurate, timely, consistent, and complete master data.
80.	Metadata management		Metadata can define as data about data or information about data
81.	Analytical		Enable users to generate on-demand reports and queries in addition to conduct analysis of data
82.	Infrastructure		Physical facilities such as computer hardware, software, networks and communications that support all shared computing resources in organizations
83.	Performance Management		Used to track the implementation of business strategy by contrasting real results against aims and objectives

S.No	Dimension /Factor	Model/Author	Description as found in Literature
84.	Balanced score card		The term "balance", mean combination set of "financial and non-financial", "leading and lagging", "internal and external", "quantitative and qualitative" and "short term and long term".
85.	Organization	TDWI Big Data Analytics MM Halper et al. (2014)	To what extent do the organizational strategy, culture, leadership, skills, and funding support a successful analytics program? Additionally, is the company organized for success in analytics? Are analytics widespread and used in everyday decisions
86.	Infrastructure		How extensive are the variety, volume, and velocity of data used in analytics, and how does the company manage its data in support of analytics
87.	Data Management		How advanced and coherent is the architecture in support of an analytics initiative? To what extent does the infrastructure support analytics for all parts of the company and potential users? What technologies are in place to support an analytics initiative and how are they integrated into the existing environment
88.	Analytics		How advanced is the company in its use of analytics? How analytics contributes to decisions made throughout the company?
89.	Governance		How coherent is the company's data governance strategy in support of its analytics program? Is the company able to manage users' data discovery and analytical explorations effectively without applying too many restrictions and getting in the way of their pursuit of insight? Program governance is important
90.	Organizational practices and culture	INFORMS analytic maturity model List et al. (2014)	Does your organization have the practices and culture to enable effective use of analytics?
91.	Analytics Capability		Does your organization possess the methods, models, and services needed to perform analytics?
92.	Data & Infrastructure		Are data sufficiently integrated and infrastructure present to support analytics?
93.	Strategic Alignment	BDMM – Big Data Maturity Model Comuzzi et al. (2016)	Effective Big Data initiatives must be sponsored by top managements and be aligned at all levels with the overall organizational strategy. This dimension measures the maturity of this alignment, identifying Strategy and Processes as the two sub-dimensions
94.	Data		Data generated by the organization. The Data domain is further broken down into the Management and Analytics sub-domains

S.No	Dimension /Factor	Model/Author	Description as found in Literature
95.	Organization		Characterized by the People and Culture sub-domains.
96.	Governance		Evaluates the extent to which organizational structures are in place to define expectations, authority, and control about the management of the Big Data capability.
97.	Technology		Technology required to extract knowledge from data effectively. The Information Technology domain comprises the Infrastructure and Information Management sub-domains
98.	Data & Analytics Vision & Strategy	Gartner's IT Score for Data & Analytics White et al. (2017)	Enterprises must have processes for developing data and analytics strategies by engaging strongly with business stakeholders, defining business outcomes and measuring the results through benefits realization
99.	Value & Outcome management		Record of where money is spent to accurately estimate work and budgeting for upcoming initiatives and programs. There is a need to monitor progress to plan and evaluate the business benefit accrued as a result of the work, to help improve the whole process.
100.	People, skills & organization		people, skills and structures in place for fostering and securing skills as well as developing their capabilities
101.	Technology & Solutions		This refers to better management skills (including vendor management). The increasing use of data and analytics platforms, integration, infrastructure and data as a service (DaaS) requires more-mature processes in these areas
102.	Implementation		Approaches to implementing change in the business, supporting solutions and coordinating delivery and support with operations
103.	Analytical model building	APMM Framework R. Grossman (2018)	data and the appropriate business requirements to produce an analytic model as the output
104.	Deploying analytic models		Processes which integrate developed analytical model into an organization's products, services, and operations in such a way as to deliver the desired business value.
105.	Analytic infrastructure		IT infrastructure required to build and deploy analytic models esp. for big data
106.	Analytic governance structure		To have seamless processes across different organizations
107.	Security and compliance for analytical assets		protecting data privacy when side channel attacks on data are growing increasingly easy; managing analytic infrastructure for big data, which can be so large that manual processes for infrastructure provisioning are no longer adequate; and following appropriate security

S.No	Dimension /Factor	Model/Author	Description as found in Literature
			and privacy procedures when working with third party data.
108.	Developing analytical strategy		Strategy to select appropriate analytical opportunities based upon available resources and short term/long term requirements and opportunities of the organization

From these 108 dimensions, it was observed that some were duplicates, some were found to be synonyms which means dimensions had different names but similar description for example, 'technology' and 'data & infrastructure'. There were dimensions with descriptions indicating a common theme for example: 'Organizational practices' and 'organization culture'. There were dimensions with related areas like data architecture, metadata management, data management, master data management, warehousing architecture. There was no clear set of distinct dimensions.

2.5 OBSERVATIONS AND RESEARCH GAPS FROM LITERATURE REVIEW

There were several observations and gaps that have emerged from literature review:

- There are twenty-nine maturity models for BI&A originated from research and practice, yet there is no single model which is a standard like the Capability Maturity Model (CMM) for software development.
- There were no clear guidelines for managers to make a decision on which of these models to use. There was not enough documentation on how to select the right model for the organization.
- There were a large number of dimensions identified from the maturity models making it difficult for a manager to select the critical ones to focus on.
- Several recent studies have focused on assessing the business value of BI&A (Krishnamoorthi and Mathew, 2018), (Trieu, 2017), (Fink et al., 2017) but not on understanding what is needed to build the BI&A capability in organizations.

- (Lautenbach et al., 2017) has conducted a study using the Technology – Organization – Environment (TOE) framework for understanding factors influencing BI&A usage extent in South African organizations. (Gürdür et al., 2018) has studied the cultural readiness, operational readiness and technological readiness of organizations to assess the data analytics readiness of Swedish organizations. (Côrte-Real et al., 2017) have conducted an empirical study with European firms to assess the value of Big Data Analytics in the organizations. (Chen and Nath, 2018) have conducted an empirical study with Chinese organizations and established the positive impact of BI&A maturity on BI&A success in the organization. There were studies found which tested BI&A maturity models in organizations in Australia, Slovenia, Poland and Bangladesh (Lukman et al., 2011), (Luftman et al., 2015). There was no empirical study found which was done in India, which is helpful in determining BI&A capability maturity of organizations in India.

- While studies have shown that the adoption of BI&A positively influences business process performance (Aydiner et al., 2019), there is insufficient empirical research about how organizations can translate their BI&A use into value for the organization (Fink et al., 2017). Where is BI&A found to be effective? Which are the topmost functions or areas of BI&A usage?

Based on the above mentioned observations and gaps in literature, this study has tried to help managers overcome the difficulty of choosing the right model to use by identifying a relevant and consolidated group of critical factors needed for assessment of BI&A capability maturity. Managers will find this helpful as identification of critical factors have a positively significant and direct influence on the BI&A systems implementation as stated by (Yeoh and Popovič, 2016). This study was based on empirical data from organizations in India. Based on the observations, one of the aims of this study was to help the organizations understand effectiveness and usage of BI&A and create a roadmap to build BI&A capability maturity.

2.6 OPERATIONAL DEFINITIONS FROM LITERATURE REVIEW

- ***BI&A capability*** describes the ability of an organization to manage the business data, for making decisions to improve operational and strategic efficiency and achieve higher business goals with the help of organizational resources such as skilled people, enterprise wide processes and infrastructure for BI&A.
- ***BI&A Maturity levels*** are a stage-wise growth path for organizations in terms of BI&A capability. The maturity level may be measured based on factors which influence BI&A.
- ***Critical success factors*** are the factors which are required to establish a robust BI&A practice. The maturity of these factors may help understand the level of the organization in terms of BI&A capability maturity. This study has brought out six critical success factors from an extensive literature review. These factors are Data Management, Enterprise processes, People Skills, Organizational Culture, Strategic alignment with BI&A and Infrastructure & Technology.

2.7 Concluding Remarks

In this chapter we discussed the overview of Maturity Models and in particular the BI&A Maturity Models. We discussed the study of the multiple dimensions found in the BI&A Maturity Models. The observations and gaps found in literature review were also discussed. In the next chapter we will discuss the research methodology adopted to address the objectives of the research.