Now and Next: A Maturity Model to Guide Analytics Growth

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Keywords: Analytics Maturity Models, Alignment, Infrastructure

1.0 Introduction

Numerous maturity models (MMs) have been developed in relation to various aspects of Information Systems (Becker et al., 2009; Mettler and Rohner, 2009). These have been used to evaluate the level of maturity of IT, data warehousing, Business Intelligence (BI), analytics, Big Data, and other emerging areas. From all these different areas, analytics is rapidly gaining recognition for its potential contributions to contemporary organisations, and so this paper focuses on the analytics maturity of organisations.

The concept of analytics is broadly understood as using data to build computer models that can be applied to products, services and processes to achieve a required outcome (Grossman, 2018). The desired outcomes include reduced risk of non-payment or cost, identified new business opportunities, understanding customer preferences, increased sales, employee performance, prospects of a health condition or a political situation etc (Siegel, 2016, pp.160-161). Analytics maturity is in turn defined as the stage of development of an organisation in its pursuit "to integrate, manage, and leverage all relevant internal and external data sources into key decision points" (Halper and Stodder, 2014).

Existing analytics maturity assessment models are recognised to cover different aspects such as data quality, leadership support, enabling processes including data management and governance, technology, people and skills amongst others. These models, however, focus on diagnosis rather than on guiding the analytics evolution in organisations and overlook the importance of IT/Analytics-Business alignment for achieving high analytics maturity.

This paper addresses these shortcomings by developing a novel maturity model which is influenced by the IT-Business alignment literature. The integrated model distinguishes between two aspects – a current "*state*" aspect which is used to access the current situation in the organisation, and a "*management*" aspect which analyses the existing processes and attitudes to establish the likely next stage of the organisation's growth in the analytics area.

2.0 Related work

2.1 Work in Analytics Maturity Models

The idea of modelling the maturity of an organisation in a specific IT-related area originates from the software process maturity framework developed by the Software Engineering Institute (SEI) in 1987, called Capability Maturity Model (CMM) (Paulk et. al., 1993). The CMM includes a set of recommendations to improve software development and maintenance capability to help the software function within the organisation to refine its software development process by first establishing the current process maturity and then identifying the most critical areas for improvement (Paulk et. al., 1993).

When this idea is applied to analytics, the concept of maturity expands beyond building and deploying analytics models; it is encompassing a range of areas including data and analytics strategy, analytics infrastructure, processes and governance (Grossman, 2018). Data availability and technical skills alone do not guarantee successful data-driven decision-making. Provost and Fawcett (2013) suggest that for a business to achieve benefits, it is a management task to create a data science and analytics culture. However, creating and nurturing an analytics culture can take years (Halper and Stodder, 2014).

Quality of data has been emphasised as an important prerequisite of analytics maturity, however, it remains a major challenge for businesses at all maturity levels (Lismont et al., 2017). This means that relevant mechanisms for ensuring data health and reliability need to be considered as a key factor in any assessment of analytics maturity.

Analytics maturity models (AMM) are known as a tool used to asses a relative position of an organisation in relation to the important characteristics of the maturity. Muller and Hart (2016) indicate that these models are designed to highlight problems that businesses face while implementing Business Intelligence (BI) and Analytics initiatives.

Our review of the existing maturity models in the BI, Analytics and Big Data space indicates that earlier ones were developed in academia with only a handful were being provided by consulting practice. Those models focused on Data Warehousing (Watson et al., 2001; Sen et al., 2012) and BI Maturity (Cates, 2005; Eckerson, 2007; Chuah, 2010). Published in 2007, the first model that addressed analytics was the DELTA model developed by Davenport (2018) and International Institute for Analytics (IIA). Other models originating from the consulting practice emerged in subsequent years, such as Gartner (2010), Capgemini (2012), INFORMS (2013), IBM (2014), TDWI (2014) and IDC (2015), often combining BI and Analytics. An overview of the identified AMMs is shown in Appendix A. Details of each of the identified and reviewed maturity models were analysed to create a set of dimensions in our Analytics Maturity Model.

Lahrmann et al. (2011) provided a theoretical model of maturity that describes five important characteristics of MMs which include the maturity concept, the dimensions, the levels, the maturity principle, and the assessment approach. A brief overview of these characteristics is provided below:

<u>Maturity Concept</u>: Lahrmann et. al. (2011) defines three different maturity concepts: “People maturity” shows the degree and availability of knowledge and skills needed to perform required activities; “Process maturity” describes how well specific processes are defined, established, managed, measured and effective; and “Object (or technology) maturity” that characterises the development level of a technology.

Dimensions: These are specific areas of interest. Ideally, each dimension is characterised by several measures such as practices, objects or activities at each maturity level.

Levels: Representative states of maturity of each dimension. Each level is identified by a unique descriptor outlining a detailed explanation of its related features.

Maturity Principle: Can be of two types, continuous or staged. The continuous type assumes scoring of activities at different levels. Staged MMs assume that all elements of any level are in place before an organisation can progress to the next level.

Assessment Approach: Qualitative assessments use descriptions, while quantitative use numeric measures.

Although the existing models can be based on different maturity concepts, dimensions and principles, as described by Lahrmann et al. (2011), they focus on analysis and may provide recommendations on continuous or staged progress in terms of setting goals. However, they do not provide a theoretical foundation for how progress should be achieved.

2.2 Research gap

Although some models have been developed by consulting practices and others were proposed by academia, the exact theoretical foundation that describes the basis for the design of the available analytics maturity models is not always provided (Lahrmann et al., 2011). A comprehensive overview of the available models by Muller and Hart (2016) also indicated that the majority of models that originated from the practice had no documentation on their foundations. Despite that many models appear to have been broadly based on the CMM framework, few analytics maturity models originate from the academia. Also, our review shows that the available models appear to use a mixed maturity concept focusing on the three elements as described by Lahrmann (2011), people, process and technology; some also incorporate organisational aspects such as vision, strategy and culture.

Analytics and maturity gap. Although, literature discusses analytics processes, data, governance and other relevant characteristics, we have not come across academic frameworks with a well-rounded interpretation of dimensions that characterise analytics maturity levels as well as suggest a transition method.

IT/Analytics-Business alignment gap. Further, although the importance of aligning Business and IT strategy has been covered in the literature extensively, the emergence and adoption of data-driven strategies by companies requires aligning IT/Analytics with the business. Analytics is seen as an element of IT supporting business decision-making and newer research indicates that investments in analytics programmes have been top IT investment priority in recent years (Liberatore et al., 2017), however we found the coverage of IT/Analytics-Business alignment in academic literature inadequate.

Functional gap. Because it is typically assumed that technology vendors use modern data technologies naturally, our initial motivation for research originated in exploring available knowledge base related to analytics maturity in technology businesses. We have identified a number of potentially interesting areas. First, there is little discussion of differences in the use of analytics techniques and processes depending on the nature of the business - every software business could potentially work differently with regards to characteristics of products, target customers, sales cycles and type of sales, for example transactional vs relationship selling. More research is needed to understand such practices and challenges. Another important factor to consider is a variety of routes to market. Since, businesses are often segmented in different go-to-markets routes such as direct business, selling through channels and online, investigating how companies can organise their analytics initiatives depending on these aspects could provide additional contributions to existing knowledge.

3.0 Developing the Analytics Maturity Framework

Given the lack of integrated models which can both assess the current maturity of an organisation and provide guidance on potential next steps for analytics development in the organisation, we set out to develop our Analytics Maturity Framework (AMF) by synthesising our findings from the literature review and a case study company, using an action design research methodology as described below.

3.1 Overall Approach – Action Design Research

For this research project, we have used the action design research (ADR) method that combines the application of theory with organisational context through gathering feedback from practitioners and users with the aim of solving an organisational challenge by designing and developing an IT artefact (Sein et al., 2011).

The ADR method deals with two challenges: 1) addressing a specific issue within the organisation by intervening and evaluating; and 2) constructing and evaluating of the IT artefact that will address the issue (Sein et al., 2011). The current research has resulted in proposing a framework that can be used to guide companies in their journey to become data-driven organisations.

The adopted research approach is grounded in the ADR method described by Sein et al., (2011) as shown on Figure 1.

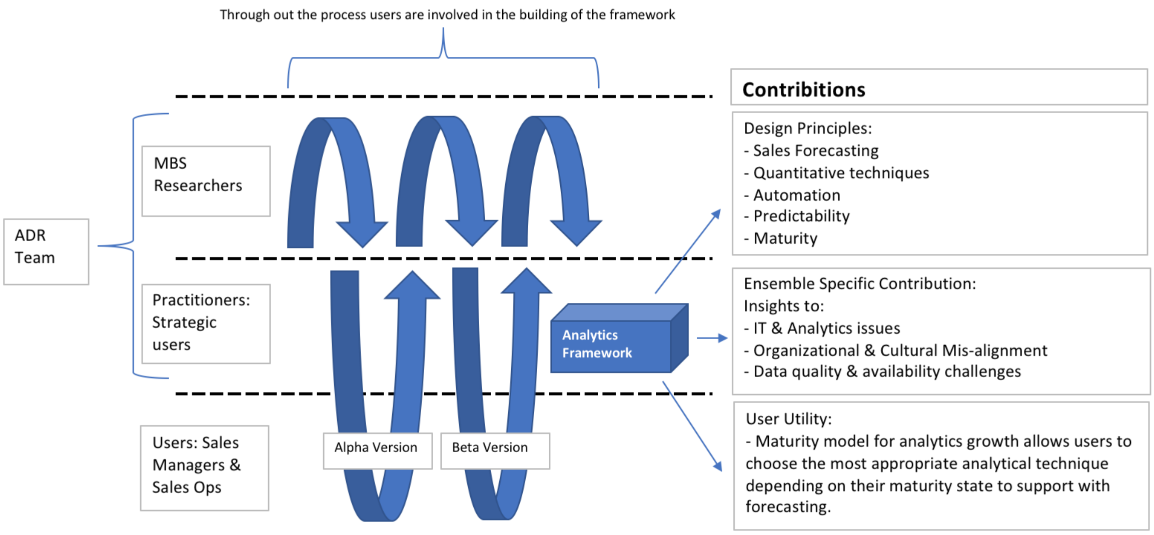

Figure 1. ADR method adapted from Sein et al. (2011)

The use of a single case study in the core of our approach permits an in-depth analysis of needs and context which are sufficiently specific yet typical for a high-tech IT company. This is triangulated with the existing knowledge about such needs provided by the literature to bring about integrated and generalised understanding of the organisational context and user needs. After each version of the artefact had been developed, we evaluated it by again drawing on both practical interviews and on theory comparison. Details are provided below.

3.2 Research Process

To explore the research question, the team used two qualitative methods concurrently, literature review and interviews. Both represent the primary input into our evaluation of the existing maturity models, their applicability to the case study company and its assessment; and their synthesis in a single model.

To guide our research progress, the following sequence of the research process phases was adapted from Sein et al. (2011) as described below:

Problem Definition: A current business problem was formulated by the practitioners from the case study company that was preparing to commence a major CRM system change. As part of this change, the company was looking at ways to build a company-wide automated sales forecasting process in order to have global upwards visibility and be a more predictive business. A business unit in question was facing challenges with streamlining the sales forecasting processes across different regions and had issues with accuracy of forecasts. This was due to internal complexities related to departmental and regional differences such as inaccurate implementation of information systems that capture data; lack of information systems adoption by employees; use of different forecasting methods by different regions; lack of predictive analytics processes; inaccuracy of input data; and the absence of global business alignment. This research proposed to assess the company’s level of development in terms of incorporating analytics and transforming this key process, so that the unified forecasting techniques could be adopted by different teams, aligned globally and implemented within the chosen CRM.

Both theory- and practice-inspired research was used here. Key information about the issue was gathered on: a) the existing process of forecasting sales and financial performance; and b) understanding of the existing practices and challenges from a practical standpoint with the case study organisation as well as literature research on the issue. During this phase, more precise business requirements were defined by the company management. These requirements were expanded on the problem definition to include improvement of forecast accuracy, better transparency and understanding of the sales forecasting process and its output; use of data and suitable analytics techniques by the business unit; reduced time for producing sales forecasts; increased sales. All these aspects were incorporated in the design of a questionnaire which we used to gather case study input during the next stage.

The **Building, Intervention and Evaluation (BIE)** stage included activities required to meet the research objectives: 1) carrying out interviews with the practitioners and users. Interview questions focused on gathering information relevant to the existing sales forecasting process and the associated practices and challenges, as well as understanding of the company's maturity level and potential improvements; 2) reviewing available maturity models by the ADR team - the researchers; and 3) integrating elements of maturity models into the target artefact.

The interviews with the practitioners, or strategic users such as global programme director and business process manager, gave insights into the circumstances of the company, established the importance of the alignment between IT and business processes, and the quality of information available to analytics systems. This additional evidence contributed to the shaping of the artefact in the iterative process. The primary source for building the new artefact was guided by organisational interventions and therefore this stage was primarily 'organisation-dominant BIE' (Sein et al., 2011). This motivated the use of the five maturity levels of Luftman and Kempaiah's Strategic Alignment Maturity (SAM) model (2007) and adapting their definitions: 'Initial', 'Committed', 'Focused', 'Managed' and 'Optimised' for the final artefact.

The synthesised model also draws on CMM's (Paulk et. al, 1993) generic description of each level's characteristics. However, we apply those characteristics specifically to the use of analytics, rather than the software development process as in the original CMM model. This is to create a synthesised definition of maturity levels instead of using individual definitions and labels provided by the evaluated AMMs.

Reflection, Learning and Formalisation of Learning are the final phases of the process, which involved validating the research project output (artefact) with the users and practitioners by presenting the model to the case study company as well as cross-checking the related research literature and formulating theoretical implications. The artefact needed to address two points: 1) it reflected preliminary designs from the researchers' theoretical perspective; and 2) it had to provide a solution to an organisational challenge from a practical perspective.

The refinement and reassessment of the research aim and objectives as part of and throughout the research process has reflected the iterative nature of the ADR process and principles.

3.3 Synthesising the framework

In this section we describe the process of synthesising the framework in further detail. Individual features of the available AMMs were used to construct representative characteristics of each of the model's maturity levels. To adhere to Lahrmann's theoretical model of maturity that implies the existence of maturity dimensions, we further developed the integrated maturity levels by devising unified dimensions, as depicted in Figure 2. In the figure we have listed three of the most recent and analytics-focused maturity models: INFORMS (Burciaga, 2013); IDC (Vesset et al., 2015) and TDWI (Halper and Stodder, 2014), yet other reviewed models from Appendix A also informed our synthesis.

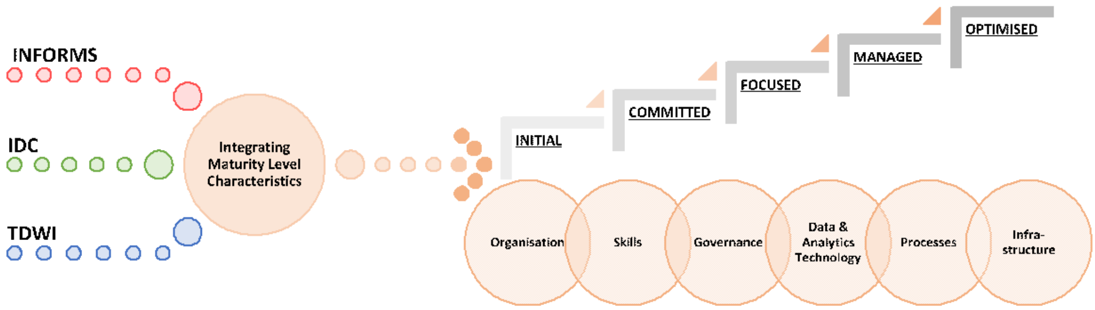

Figure 2. Integrating Maturity Level Characteristics; input maturity models are defined in Appendix A.

To do so, we adapted the IT/Analytics-Business Alignment Maturity Criteria from the SAM model (Luftman, 2000, 2007). Although the original criteria describe strategic alignment between IT and Business, our adapted version, which is outlined further, focuses primarily on IT/Analytics-Business Alignment whereby Analytics is a function of IT.

We highlight three reasons for the adaptation of the SAM model for standardised measures (criteria) of Maturity Levels and Dimensions in our research model. First, it emphasises the 'use of analytics' for solving business problems. Second, since the theoretical basis for the reviewed AMMs was not provided by the models, this approach offered the underpinning foundation and consistency. Finally, although the three selected models agreed on certain elements as part of maturity characteristics, using multiple dimensions from the individual models presented difficulties in characterising integrated maturity levels.

Having defined the similarity to Luftman's SAM model, grouping or clustering of dimensions was based on commonly occurred themes for each maturity level of the integrated model. Furthermore, six criteria indicating IT/Analytics – Business Alignment maturity were selected based on the premise that while each criterion is important, alone it is insufficient; alignment will be achieved when all the elements are in place, nurtured, monitored and revised. The process of creating IT/Analytics – Business Alignment Criteria is shown in Figure 3.

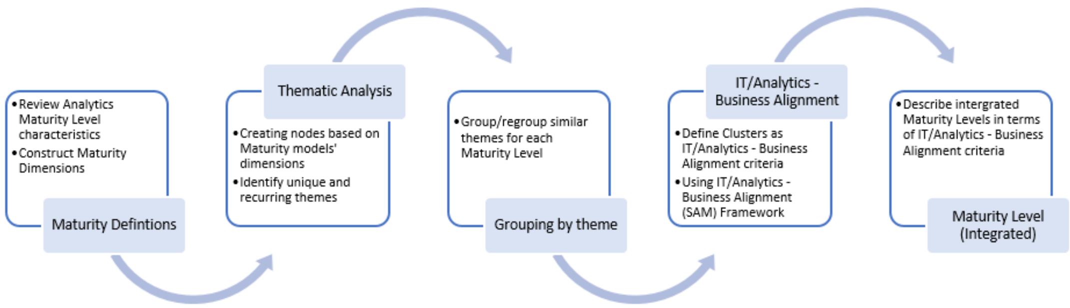

Figure 3. Creating Alignment Dimensions Process

The need to create standardised dimensions was also supported by findings from the interviews. IT/Analytics – Business alignment, capability and maturity came up as some of the current challenges within the case study company in our interview findings. For example, IT systems were not ready to accommodate the concerned business unit's forecasting process across all regions which represented a challenge for the relevant staff. While the use of predictive modelling was desired by the functional business units, the state of the IT infrastructure did not allow for such integration, indicating IT/Analytics-Business misalignment. Also, the availability of analytics resources existed within individual business units; analytics processes were not established in some regions, while other regions utilised both, skills and processes on the departmental level.

Following the ADR process and principles, we looked at ways of incorporating these findings and feedback from the practitioners and users into our research model; and then feeding the organisational contextual information into the analysis in order to refine the development of the framework (artefact).

As a result, creating well-defined synthesised Maturity Levels and their criteria describing the characteristics of each stage of maturity aided us in generating our recommendations to the company.

4.0 Details of the Analytics Maturity Framework

4.1 IT/Analytics – Business Alignment and Maturity Dimensions

Our ‘IT/Analytics-Business Alignment’ model is adapted from Luftman and Kempaiah (2007) and consists of six dimensions that are indicative of the IT/Analytics – Business alignment as described below:

Organisation: Defines to what extent the organisational strategy, culture, leadership, skills and funding backs analytics initiatives. Demonstrates the support of Information Technology, Information Systems and Analytics to the business as well as it reflects the awareness of the benefits of the use of analytics across the organisation (fragmented, Business Unite-level or widespread). Is Analytics used in everyday decision making?

IT & Analytics Infrastructure: Defines the level of suitability of the infrastructure and platform/ architecture development in support of analytics programmes. Demonstrates the ability of the infrastructure to support large volumes of data and integrate additional data for all relevant business operations and users.

Analytics Processes: Demonstrates how extensive data characteristics (variety, velocity, timeliness, quality) used in analytics are. Defines the existence of data and analytics processes and how the organisation manages them.

Skills: Demonstrates what level of data and analytics skills exist in the organisation to work with current and future technologies. Assesses necessary practices such as acquisition, retention, training, skills development, etc. as well as capability for learning.

Governance: Defines who has an authority to make decisions related to governance of analytics. Demonstrates how coherent and supportive of analytics programmes the company's data governance strategy is.

Data & Analytics Technologies: Demonstrates how advanced the organisation is in the use of analytics technologies, tools and techniques. How analytics are used and delivered. Attitude of the organisation to analytics process management and metrics, how standardised the analytics processes are and how they are integrated with key business processes and decisions.

4.2 Five Levels of Analytics Maturity

Maturity levels of the integrated AMF and their description in terms of the six dimensions adapted from the SAM framework are presented in Section 5.0.

The framework consists of the following components:

1. Five Analytics Maturity Levels;
2. Six IT/Analytics – Business Strategic Alignment dimensions that characterise each maturity level. Each dimension was further evaluated with the following aspects:

   A: Management. This characterises the existing processes and the considerations the business makes regarding analytics within the context of each maturity level;

   B: State. Qualitative assessment of what the business currently uses and what capabilities it has (e.g infrastructure, technology, skills, processes);
3. Transition to the next maturity level.

5.0 Using the framework to guide analytics growth

5.1 Role of both aspects in the framework

The framework distinguishes between two aspects of analytics maturity at each level – a present "State" aspect which is used to access the current situation in the organisation, and a "Management" aspect which analyses existing processes and attitudes to establishing the next stage of the organisation's growth in the analytics area. The presence of these two aspects makes our proposed framework unique among those reviewed and allows us to use it for both analysing the existing situation and for guiding the transition towards the higher levels of maturity. The visualisation of the framework and the aspect of the analytics growth are provided in Figure 4. Full details are available at **https://bit.ly/2GogTmn**

Dimensions and Aspects of Maturity: A: Management B: Present State	Inintial	Commited	Focused	Managed	Optimised
Organisation: A: Analytics Strategy — what the organisation is doing about it, management attitude towards Analytics Strategy B: Business question — what is the current business problem(s) that need to be addresses with Analytics?	No analytics awareness	Consideration of analytics benefits	Identifying problems to solve with annalytics	Management support, growing culture, developing a company-wide Analytics Strategy	Analytics critical for the business, Enterprise-wide Analytics Strategy
IT&A Infrastructure A: Attitude to dedicated infrastructure B: Volume that can be handled by the existing infrastructure, platform development	Enterprise architecture does not support analytics, only business functions	Ccnsider IT support for selected business issues with Analytics	Attempts to unify architecture, considering available technologies e.g. cloud or Hadoop	The infrastructure is unified to underpin analytics, analytics ecosystem	Coherent, fully operational Analytics infrastructure is used in the mission-critical aspects of the business
Analytics Processes: A: Process management B: Data characteristics (variety, velocity, timeliness, quality)	Processes are siloed, not focused on data & analytics	No formal processes; no pro-active data collection for Analytics initiatives	Initial attempts to monitor progress and document processes and outcomes	Analytics processes are automated and intergrated with other business processes	Standardised processes are established; integrated with all key business processes & decisions
Skills: A: Processes and attitudes to future analytics skills B: Current skills level (skills — Beginner, Intermediate, Advanced)	Skills suitable to address business questions, analytics enthusiasts. Begginer level	Some of the necessary technology and analytics skills, but no exisitng data/analytics propfessionals	Skills acquisition and training on BU level, Intermediate level, what skills are needed	The need for in-house analytics capabilities and skills, active acquisition of experienced skill	Advanced skills, established data science teams, established Centres of Excelence
Governance: A: Data Governance processes (what is being done about the data governance processes/strategy?) B: Data Granularity & Source (level of data granularity, data source): Transactions, Customers, Market, Geography	No data management strategy, governance in place	Governance is fragmented, project-based	BU-focused data strategy and management	Ad hoc basis, development of business wide data governance strategy	Full analytics/data strategy is well-established and governance used routinely to create value
Data & Analytics Technologies: A: Use of technologies (how technologies are used, strategic development of technologies?) B: Current availability (what technologies are currently used?)	Use of technologies by BU to address a specific function, siloed	New technology can be acquired and used for a specific project	Need to develop a framework for selecting suitable application, technologies and techniques	Range of technologies, variety of platforms support Analytics programmes	Centralised approach to select methods, software, and hardware for various problems

Figure 4. Maturity Levels' Dimensions and Characteristics in the Proposed Analytics Maturity Framework, including Aspects of Maturity

5.2 Moving through stages of the analytics maturity using the framework

The transition model can be applied to any Dimension/Maturity Level in the framework. It is used to guide the organisation's progress from any current level of maturity to more advanced.

The transition begins from the present state B_t as assessed by the "State" aspect of a specific maturity dimension. If a higher maturity state B_{t+1} is desired, the organisation should initiate the transition by changing its current assessment A_t according to the "Management" aspect of the same dimension to the one associated with the desired higher level of maturity A_{t+1}. This transition is represented by the arched arrow inside the diagram in Figure 5. The underlying assumption is that the current analytics maturity level is a result of the current practices and attitudes measured by the "Management" aspect, as represented by the vertical arrow on the right of Figure 5.

The change, for example, should centre around embracing relevant analytics and governance strategy, or hiring strategies, etc. As the sophistication of infrastructure, technology and techniques grows, and the implementation of the analytics strategy, governance and processes support the business requirements, the desired "future" state B_{t+1} and management maturity assessment become a reality; this will be now considered as "present" state and management maturity, which is shown by the backward arrow on the outside of the diagram. The previously-defined aspirations are achieved and so to progress towards creating a new "future" state of analytics maturity, the "management maturity" should change again. This is a continuous spiral-like cycle.

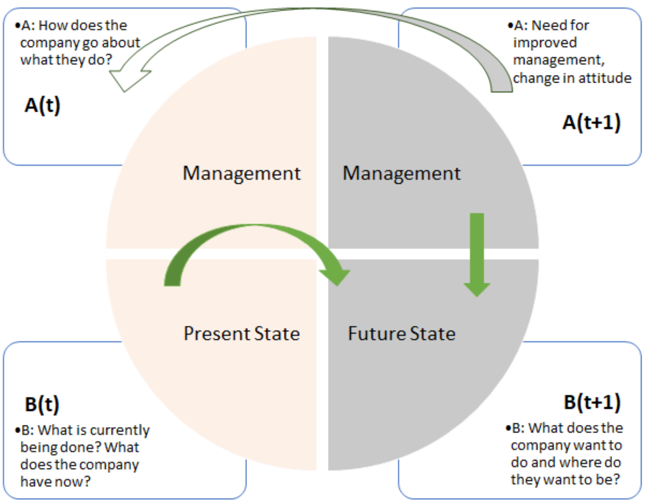

Figure 5. **Transition model**

6.0 Assessing the framework and its advisory component

6.1 Approach for gathering feedback

To gather feedback on the framework we presented our findings and the maturity model to senior managers within the case study company. In addition, this framework was also shown to three Operations, Process and IT Managers within external companies to obtain their opinion about the usefulness and relevancy. One company is an early-stage start-up with no global footprint and another is slightly more mature with the global footprint.

All managers were surveyed after the presentation delivered over a series of conference calls and face to face discussions. The presentations focused on explaining what the framework is, why it has been created and how this could support their business. This was followed by a set of questions to the participants to understand how their businesses could use this framework.

6.2 Feedback summary

When asked whether the framework was useful five interviewees across three companies agreed this was very useful for reasons such as gaining an understanding of the current state of their business. More importantly, they were able to understand what the desired state should be and start building initiatives in their roadmaps to achieve a desired level, and bring in the right people for projects. The respondents found the framework clear as they were able to identify what analytics maturity level their business was at. When asked whether it could help them select the right analytics technique, the general response was positive since it worked at a high level; however, it was indicated that there was a need to incorporate other elements such as the nature of the business and the data collected. Also, when asked whether the framework provided guidance on how to move to a certain maturity level, some respondents said it only provided them with identifiable maturity characteristics at each level, but not with ‘this is what you need to do’ help to move to the next levels. Overall, all respondents found it practical and would use this framework in their business.

7.0 Conclusion and Summary

7.1 Summary

Our approach to this research question of how a business process can be transformed from intuition-led into data-driven and what maturity development strategy organisations can use has been based on the principles of the Action Design Research method. We have used an extensive knowledge base of available methods, frameworks and models. We explored available analytics maturity models and evaluated them from the perspective of the theoretical model of maturity. To be able to apply the existing knowledge to the real business problem and build a solution suitable for the organisational context, we investigated company challenges through interviews with key knowledge holders from within the case study company. We also learned that IT systems used across different regions did not accommodate the needs of the forecasting process for the business unit in question. In addition, while there was awareness of how analytics could be leveraged across the business, the lack of well-established analytics strategy, clearly-defined analytics processes and governance was the barrier to a wider use of analytics in sales forecasting, and potentially in other processes. Having completed the analytics maturity assessments, we synthesised the characteristics of maturity levels from three maturity models to generate an integrated model. We derived five analytics maturity levels from our synthesis and this new framework is based on the principles of the IT-Business Strategic Alignment Maturity. The six criteria, called Dimensions, that characterise each Maturity Level in this framework have been designed by grouping commonly occurred themes and while they were adapted from Luftman’s SAM model (2000, 2007), the primary focus of the alignment is the analytics space. Although, businesses will always want to know what happened and how they perform over a period of time, data-driven decision making incorporating predictive and prescriptive modelling is becoming more pervasive. This creates new challenges: data quality, unification and governance are becoming primary issues that need to be addressed by the management. Furthermore, the attitude towards the present state of the analytics strategy, infrastructure, skills, analytics processes and governance directly affect the choice of analytics techniques. The observation is that the more mature companies can apply a wider range of analytics technologies and techniques to address a broader pool of business questions and opportunities. These techniques are machine learning algorithms, and while in some cases they may underperform traditional statistical techniques (Makridakis et al., 2018), they are more capable of dealing with the ever-growing data volume and scale. Our framework provides a way of positioning the business in relation to the maturity level and assessing the IT/Analytics-Business Alignment. It further proposes a transition move to a desired state, to achieve analytics maturity growth. It has been validated with Senior Managers from the case study company and external companies through discussions of usefulness of the framework, the challenging areas and whether the business can be correctly positioned within the analytics maturity levels. It was agreed that the issues identified with the use of the proposed framework required closer attention by the management.

7.2 Limitations and further work

While applying the proposed framework on the cases study company was the primary purpose of this research project, we acknowledge that drawing on only one case study with some limited external validation provides insufficient basis to claim general applicability. Therefore, we recognise that further development and refinement is needed and there might be additional opportunities to extend this work. In a similar fashion, further potential exists in investigating the suitability of IT infrastructure and architecture to the maturity levels. Many companies run on legacy IT infrastructure and systems which might not be suitable for the modern data-driven business environment. In the future research, an in-depth investigation of other dimensions, for example analytics processes or governance, represents a potential opportunity since even the organisations at the highest maturity levels experience challenges with standardisation. We also recognise feedback from the validation exercise, that the transition move should be clearly explained in order to achieve desired maturity growth, especially given that this framework presumes a continuous maturity principle.

7.3 Contributions

The outcome of this research presents a number of important implications, both theoretical and practical. In the theoretical domain, this research covers the identified literature gaps relating to the absence of comprehensive analytics maturity frameworks from the academia in recent years. The proposed framework provides a theoretical foundation for characteristics that describe maturity. It also suggests a transition method that takes into account the present state and organisational attitude towards the use of analytics; and also the future state of a desired maturity level. The research addresses the IT/Analytics-Business alignment, whereby Analytics is an important IT element, illustrated through the six dimensions which should be mutually inclusive to achieve the business strategy, IT and Analytics alignment for a data-driven business. Although we have not fully covered the functional gap to address the nature of the business (e.g. transactional volume, or large but infrequent deals) as an important element defining the right analytics processes, this is a potential topic that can be further investigated.

In the practical or managerial domain, the framework provides a qualitative assessment tool for business managers helping to understand their organisation's stage of development in relation to implementing analytics for decision making as part of a data-driven transformation. Business leaders could use this framework to plan actions and set goals. For example:

<u>Short term goals</u>: to form an understanding of their current environment and maturity level so that they can build the right analytics processes, environment, governance and select suitable data technologies and analytics techniques;

<u>Long term goals</u>: to form an understanding of current state as well as a desired analytics maturity state and design a move to the next level.

We believe this framework provides a comprehensive approach to identifying the analytics maturity level and dimensions that need to be addressed so business could achieve their analytics growth.

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Appendix A. Maturity Models Overview

No	Name	Reference	Addressed topics
1	INFORMS	Burciaga, 2013	Organisational practices and culture; analytics capability, data & infrastructure. This is analytics-focused model
2	IDC	Vesset et al., 2015	Maturity concept focuses on people, processes and technology across five dimensions: vision, technology, data, people, process
3	TDWI	Halper F. and Stodder, D., 2014	TDWI (The Data Warehousing Institute) Analytics maturity measures the ability of businesses to expand their analytics capabilities in terms of technologies, data management, analytics, governance, and organisational aspects
4	PAFMA	Capgemini, 2012	Predictive Analytics Maturity Framework Assessment (PAMFA) examines maturity in terms of technology environment and the organisation’s ability to adopt analytics. The model looks at the adequacy of people, processes, deployment, prioritisation and governance for analytics purposes
5	Gartner	Howson, C. and Duncan, D., 2015	The Gartner model identifies the level of development BI and analytics initiative must reach in order to support enterprise goals
6	IIA AMA	IIA, no date	The Analytics Maturity Assessment (AMA) is based on DELTA model (2007). It measures how well an organisation uses analytics to increase revenue, reduce costs, optimise performance and improve overall decision-making. The main concept is on business issues such as analytics strategy, non-data driven corporate cultures, poor processes, organisational resistance, quality and availability of data. The updated model (2017) includes two new components: technology & analytics techniques
7	APMM	Grossman, R., 2018	The Analytic Processes Maturity Model (APMM) identifies analytics-related processes in six key process areas: i) building analytic models; ii) deploying analytic models; iii) managing and operating analytic infrastructure; iv) protecting analytic assets through appropriate policies; v) operating an analytic governance structure; and vi) identifying analytic opportunities, making decisions and allocating resources based on an analytic strategy
8	EBIMM	Chuah, M-H., 2010	The Enterprise Business Intelligence Maturity Model (EBIMM) model offers a set of dimensions comprising of data warehousing, information quality, knowledge process to evaluate the maturity levels of Enterprise Business Intelligence. The model is based on the CMM framework
9	DWPM	Sen et al., 2012	The Data Warehousing Process Maturity (DWPM) model uses the CMM principle for a continuously evolving data warehousing process in an organisation supporting quality and timely delivery of information
10	LOBI	Cates et al., 2005	Ladder of Business Intelligence (LOBI) is a framework for enterprise IT planning and architecture
11	IBM	Nott, C., 2014	IBM Big Data & Analytics Maturity Model focuses on business strategy, information, analytics, culture, architecture, governance
12	'Stage growth' model	Watson et al., 2001	The model uses the 'stages of growth' concept widely used in organisational and IS research. It is based on the premise that things change over time, in both sequential and predictable ways