IBIMA Publishing
Communications of the IBIMA
http://www.ibimapublishing.com/journals/CIBIMA/cibima.html
Vol. 2011 (2011), Article ID 417812, 11 pages
DOI: 10.5171/2011.417812

A Maturity Model of Enterprise Business Intelligence

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Abstract

The implementation of an enterprise-level business intelligence initiative is a large-scale and complex undertaking, involving significant expenditure and multiple stakeholders over a lengthy period. It is therefore imperative to have systematic guidelines for business intelligence stakeholders in referring business intelligence maturity levels. Draw upon the prudent concepts of the Capability Maturity Model, this research proposes a multi-dimensional maturity model with distinct maturity levels for managing enterprise business intelligence initiatives. The maturity model, named Enterprise Business Intelligence Maturiy (EBIM), consists of five core maturity levels and four key dimensions, namely information quality, master data management, warehousing architecture, and analytics. It can be used to assist enterprises in benchmarking their business intelligence maturity level and identifying the critical areas to attain higher level of maturity.

Keywords: Enterprise Business Intelligence, Maturity Model, Survey

Introduction

Recently, business intelligence (BI) market has experienced high growth and BI technologies have consistently received attention by many Chief Information Officers (Gartner 2007; Gartner 2008; Gartner 2009). According to Wixom and Watson (2010), business intelligence is “a broad category of technologies, applications, and processes for gathering, storing, accessing, and analysing data to help its users make better decisions”. The major objective of a business intelligence application is to embrace “intelligent exploration, integration, aggregation and a multidimensional analysis of data originating from various information resources” (Olszak and Ziemba 2007). Hence, data is transformed from quantity to quality (Gangadharan and Swami 2004). In other words, information from many different sources is integrated into a coherent body for strategic planning and enhanced decision support. Meaningful information can be delivered at the right time, at the right location, and in the right form. As a result, business intelligence can be used to improve decision making process.

The whole enterprise business intelligence project planning and implementation always involve a significant amount of resources and various organisational stakeholders over a period of years (Wixom and Watson 2010). While the importance of business intelligence application is becoming more widely accepted, there is a limited study to provide systematic guidelines for such resourceful initiative. Therefore, this research seeks to bridge the gap that exists between academia and practitioners by

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investigating the dimensions and associated factors for each maturity level in enterprise business intelligence implementations. Based on the investigation results and the concepts of Capability Maturity Model (CMM) (Paulk et al. 1993; Paulk et al. 2003), the authors aim to develop an Enterprise Business Intelligence Maturity (EBIM) Model that may help organisations in assessing existing enterprise-scale business intelligence implementation and identifying potential weak points and improvement strategies.

It is expected that this research will make a contribution to both theory and practice. In theoretical terms, this research: adds to knowledge and contributes to the literature of an emerging area of interest – the management of enterprise business intelligence initiative, in particular, an enterprise-level business intelligence maturity model for better guidance in such resourceful and complex undertaking; identifies the dimensions and associated factors which constitute the EBIM model; examines previous literature on the ways in which Capability Maturity Model constructs could be applied accordingly, in particular, data warehousing, information quality, analytics and business intelligence studies. In practical terms, the project explores and defines an enterprise business intelligence-specific maturity model, so enabling business intelligence stakeholders to better plan, assess, and manage their respective business intelligence initiatives.

The remainder of this paper has been structured as follows: The next section presents literature review of this research project and then proceeds by explaining the research methodology used for building the rigorous EBIM model in Section 2. Section 3 outlines and discusses the factors of the EBIM model. The fourth section presents the overall discussion, and finally, the conclusion of the study.

Literature Review

The concepts of CMM were developed by Software Engineering Institute of Carnegie Mellon University. The model is based on actual practices in software industry and reflects the state of art in software engineering, as well as the needs of personnel performing software process appraisals (Paulk et al. 1993; Paulk et al. 2003). CMM is a process improvement approach that provides organisations with the essential elements of effective processes. It can be used to guide process improvement across a project, a division, or an entire enterprise. CMM helps in integrating traditionally separate organisational functions, setting process improvement goals and priorities, giving guidance for quality processes, and providing a point of reference for appraising current processes. In brief, it offers a set of guidelines to improve an organisation's processes within an important area (Wang and Lee 2008).

To date, numerous studies have been conducted based on the foundation of CMM. For instance, a safety extension to the CMM has helped the Australian Department of Defence in assessing the organisation's capability for developing safety related systems (Bofinger, Robinson and Lindsay 2002). While Li (2007) employed CMM approach to provide organisations with the essential elements of effective processes, Daneshgar, Ramarathinam and Ray (2008) adapted an IT service CMM to address the appropriate levels of collaboration and knowledge sharing in organisations, whereas Sen and Ramamurthy (2006) developed a data warehousing process maturity based on CMM. In view of all these studies and to better understand the problems affecting enterprise business intelligence initiative, the business intelligence stakeholders should try to focus on enterprise business intelligence endeavour as an enterprise-wide process, along the lines of the CMM concepts. A set of critical associated factors recognized from extant literature review are grouped into a five-level capability maturity model to form a holistic approach for enterprise-level business intelligence maturity. It is believed that the adaption of Capability Maturity Model into EBIM model is appropriate in addressing suitable level of EBIM model.

Building the EBI Maturity Model

The CMM is a well-established and widely-recognised model that characterizes an organisation's software development maturity based on their practices. However, it does not address the maturity of firms with regard to the manner in which enterprise-scale business intelligence is managed. In response to this, the research aims to identify the respective factors for each level of the maturity model that have a bearing on enterprise business intelligence maturity. Based on the literature of information quality, master data management, warehousing architecture, and analytics and draw upon the work of Baskarada, Koronios and Gao (2007), Dyche and Levy (2009), Eckerson (2009), and Davenport and Harris (2007) that are closely related to the requirement of a successful business intelligence program, a conceptual model was synthesised and developed for further empirical research using quantitative methodology. That is, the conceptual model would be validated via a large-scale structured questionnaire survey. In this study, within the respective four key dimensions and five levels of maturity, a total of twenty critical factors were generated for the survey instrument. The factors were evaluated using seven-point Likert scale ranging from 7 being "strongly agree" to 1 being "strongly disagree". The survey was distributed by email to 75 international business intelligence practitioners where a total of 18 responses were received, giving a response rate of 24%.

Figure 1 depicts the EBIM model that can be employed for managing an enterprise business intelligence initiative. The characteristics of each evolutionary maturity level along with the four key dimensions are described in the following sub-sections:

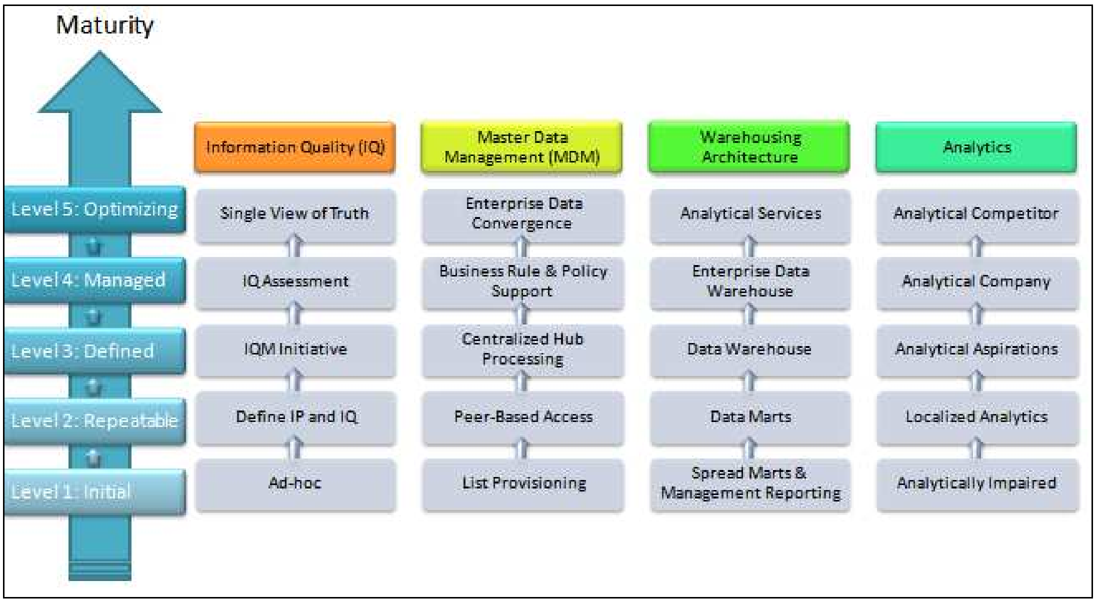

Fig 1. The Enterprise Business Intelligence Maturity (EBIM) Model (Source: Developed by authors)

Level 1 – Initial

- ***Information Quality: Ad-Hoc***

Information Management (IM)/Information Quality Management (IQM) processes are not standardized or documented during this stage. There is no awareness of any information quality (IQ) issues, therefore no attempts are made to assess or improve information quality. Organisation acts in response only when information quality problems occur.

- ***Master Data Management: List Provisioning***

There is no systematic and thorough way of ensuring changes to the master list. Defining and maintaining master lists involve significant meetings and human interaction. Data conflicts, deletions, changes, explaining data file formats, and content details are handled manually. Individual applications must understand how to navigate to the master list.

- ***Warehousing Architecture: Spread Marts & Management Reporting***

Management reports are static reports which are printed and disseminated to employees on weekly, monthly, or quarterly. Spread marts are spreadsheets or desktop databases that function as surrogate data marts.

- ***Analytics: Analytically Impaired***

The company has some data and management interest in analytics.

Level 2 - Repeatable

- ***Information Quality: Define IP and IQ***

All Information Product (IP) and Information Quality (IQ) requirements have been identified and documented. Accordingly, related information quality dimensions and requirements have been classified.

- ***Master Data Management: Peer-Based Access***

There is hardcoded logic for applications to interact with the list of master data. A data model is created to identify each master record distinctively. Individual applications take responsibility to maintain the master list. All data and integrity rules are copied to new integrated application systems.

- ***Warehousing Architecture: Data Marts***

A data mart is an analytical data store that generally focuses on specific business function within an organisation, e.g. department. Data marts are tailored to meet the needs of data users. Usually interactive reporting tools such OLAP and ad hoc query tool are used to access the data marts to gain deeper insight.

- ***Analytics: Localized Analytics***

Functional management builds analytics momentum and executives' interest through applications of basic analytics.

Level 3 - Defined

- ***Information Quality: IQM Initiative***

In this stage, information quality management is treated as a core business activity and widely implemented across organisation.

- ***Master Data Management: Centralized Hub Processing***

In brief, everything is centralized during this stage. Master reference data, business-oriented data rules, and connected processing are centrally handled. Cross-functional or cross-organisation conflict can be resolved by a data governance process. Thus, data accuracy and consistency is guaranteed.

- ***Warehousing architecture: Data Warehouse***

A data warehouse provides interactive reporting and deeper analysis. New insights are promised due to the capability of cross-functional boundaries query.

- ***Analytics: Analytical Aspirations***

Executives commit to analytics by aligning resources and setting a timetable to build a broad analytical capability.

Level 4 – Managed

- ***Information quality: IQ Assessment***

Information quality metrics have been developed and information quality is being evaluated.

- ***Master Data Management: Business Rules & Policy Support***

A process-driven data governance framework exists to maintain centralized business rules management and distributed rules processing. Organisation has a mature change management process. SOA is applied to integrate common business methods and data across applications. There is an automated way to both enforce and undo changes to master reference data.

- ***Warehousing Architecture: Enterprise Data Warehouse***

Enterprise data warehouse acts as an integration machine that continuously merges all other analytic structures into itself. The enterprise data warehouse helps organisation to achieve a single version of the truth.

- ***Analytics: Analytical Company***

Analytic capability draws most attention from company top executives, thus enterprise-wide analytics capability is being developed.

Level 5 – Optimizing

- ***Information Quality: Single View of Truth***

Source of information quality problems have been recognised. There are continuous initiatives to improve processing of information quality problems. Besides, impact of poor information quality has been calculated.

- ***Master Data Management: Enterprise Data Convergence***

In this stage, the hub is fully integrated into the application system environment. The hub will propagate data changes to all the application systems that need the master data. Application processing occur without depending on physical system location and data navigation.

- ***Warehousing Architecture: Analytical Services***

Gradually, the enterprise data warehouse value increases as its visibility declines. Enterprise data warehouse fades into the background as a business intelligence service. Examples of analytical services are interactive extranets, web Services, decision engines and so forth.

- ***Analytics: Analytical Competitor***

The enterprise-wide analytics capability promises the company regular benefits. The company focuses on continuous analytics review and enhancement.

Discussion

In order to attain validity and reliability for the survey results, divergence in demographics and heterogeneous backgrounds of participants in business intelligence are authenticated. Likewise, triangulation of data using multiple sources of information ensures external validity in this research. Respondents from various backgrounds, occupation, age, gender and so on are selected for the survey. Thus, validity and reliability of results are obtained. Moreover, use of average variance extracted method assures discriminant validity. Subsequently, a more holistic result can be acquired.

Table 1: Confirmatory Factor Analyses of the EBIM Model (Source: Developed by authors)

Dimensions	Associated factors	Standardized Loadings	Minimum	Maximum	Mean	Standard Deviation	Average Variance Extracted (AVE)
Information Quality (IQ)	Ad-hoc	0.76	2	7	5.33	1.53	0.64
	Define IP and IQ	0.57	1	7	4.00	1.78	
	IQM Initiative	0.59	1	7	4.11	1.75	
	IQ Assessment	0.61	1	7	4.28	1.96	
	Single View of Truth	0.67	1	7	4.72	1.87	
Master Data Management (MDM)	List Provisioning	0.52	1	6	3.67	1.88	0.67
	Peer-Based Access	0.75	2	7	5.28	1.41	
	Centralized Processing	0.67	1	7	4.67	1.78	
	Business Rule & Policy Support	0.68	2	7	4.78	1.52	
	Enterprise Data Convergence	0.72	1	7	5.06	1.63	
Warehousing Architecture	Spread Marts & Management Reporting	0.70	3	7	4.89	1.23	0.72
	Data Marts	0.75	2	7	5.28	1.32	
	Data Warehouse	0.75	2	7	5.28	1.45	
	Enterprise Data Warehouse	0.70	2	7	4.89	1.41	
	Analytical Services	0.69	2	7	4.83	1.47	
Analytics	Analytically Impaired	0.75	2	7	5.22	1.63	0.74
	Localized Analytics	0.79	2	7	5.56	1.29	
	Analytical Aspirations	0.73	2	7	5.11	1.41	
	Analytical Company	0.73	1	7	5.11	1.97	
	Analytical Competitor	0.70	2	7	4.89	1.75	

Based on the survey result, a systematic and rigorously- studied EBIM model for managing the complex and resourceful enterprise-scale business intelligence initiative has been produced. In order to ensure discriminant validity, a confirmatory factor analysis was performed to analyse the collected data. It appeared that the average variance extracted (AVE) values for each of the critical factors exceeds 0.5, hence, the finding established the discriminant validity for this research (Fornell and Lacker 1981), as indicated in Table 1. The data in Table 1 also shows that the means vary between 5.56 for "Localized Analytics" and 3.67 for "List Provisioning". The highest mean was found in analytics associated factors while the lowest was in the master data management construct. The column of mean indicates a negative skewed distribution because most of the factors are at least one scale point to the right of the centre of the scale. Standard deviations vary between 1.23 for "Spread Marts & Management Reporting" in data warehousing construct and 1.97 for "Analytical Company" in analytics construct.

As illustrated in Figure 1, the management of a successful enterprise business intelligence initiative is a function of four major dimensions namely; information quality, master data management, warehousing architecture, and analytics, all working in concert. An organisation's enterprise-level business intelligence maturity can be reasonably mapped in five evolutionary levels along these dimensions. Each maturity level is a prerequisite to the next higher one. Therefore, each higher maturity level encompasses all previous lower levels. For instance, a company at a level 3 maturity level embraces the important factors of level 1 and level 2.

However, a firm with a level 1 information quality and a level 3 warehousing architecture would still be classified as level 1. In other words, any misalignment of evolutionary progress would lead to a dimension tension and thus, suboptimal outcome (Davis, Miller and Russel 2006). This is because being the weakest link, the lagging evolutionary dimension (for instance, a level 1 information quality) will affect and reduce merits of other more mature dimensions.

Conclusion

Although the business intelligence applications have been the primary agenda for many Chief Information Officers, the literature review on related works indicates little academic research on the maturity model for a successful enterprise-scale business intelligence implementation. This study presents the first rigorously research step towards understanding the key dimensions and associated factors influencing enterprise-level business intelligence maturity. Draw upon the CMM concept and the relevant literature on business intelligence, the EBIM model was developed. The CMM was productively adapted into the enterprise business intelligence implementation via this research work and this extends the knowledge related to contemporary enterprise business intelligence systems.

From a practical standpoint, the EBIM model provides a fundamental framework for an enterprise not only to assess where it is in its evolutionary continuum of maturity, but also to identify the existing problems and plan a systematic path for evolving into higher levels of maturity. The study constitutes an important development in knowledge about critical factors impacting enterprise-scale business intelligence initiative. By successfully identifying the issues and criteria which determine the success of enterprise business intelligence systems implementation, the EBIM model and associated multidimensional factors allow business intelligence stakeholders to holistically understand the issues that impact on implementation of enterprise-level business intelligence. Furthermore, the model also allows business intelligence stakeholders to better use their scarce resources by focusing on those key areas that are most likely to have a greater impact.

This research work is just a preliminary work and it is expected that the research being carried on by conducting another survey which involves a large sample size. Hence, the findings of further research would overstep the limitation in terms of generalisability and to be more representative. Moreover, an interactive software will be developed to offer a user-friendly tool for assessing and presenting the maturity level in a convenient way.

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Appendix

Enterprise Business Intelligence Maturity (EBIM) Model Survey

All replies are confidential.

Name : ____________________
Designation : ____________________
Email : ____________________
Organization : ____________________

Which best describes your organization's primary INDUSTRY?

What are the annual revenues of your organization?

Where is your organization LOCATED?

Enterprise Business Intelligence Maturity (EBIM) Model

Please rate each item by crossing the box under 1, 2, 3, 4, 5, 6 or 7. Select one answer per row.

Strongly Disagree	Disagree	Somewhat Disagree	Neither Disagree nor Agree	Somewhat Agree	Agree	Strongly Agree
1	2	3	4	5	6	7

Information Quality (IQ)							
Ad-hoc IM/IQM processes are not standardized or documented. Organization is only reacting to IQ problems as they occur	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Define IP and IQ All Information Products (IP), together with their quality requirements, have been defined and documented.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
IQM Initiative IQM is being considered as a core business activity. Organization-wide IQM initiative has been established	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
IQ Assessment IQ metrics have been developed and IQ is being assessed.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Single View of Truth Root causes of IQ problems have been identified and impact of poor IQ has been calculated.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Master Data Management (MDM)							
List Provisioning There is no systematic way to manipulate the master list. Data conflicts, deletions, and changes are handled manually.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐

Peer-based Access Data access and integrity rules exist, but must be managed by the individual application systems.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Centralized Hub Processing Master reference data is centrally managed. The hub is ensuring data accuracy and consistency.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Business Rule and Policy Support A process-driven data governance framework used to supports centralized business rules management and distributed rules processing.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Enterprise Data Convergence The hub is fully integrated into the application system environment, propagating data changes to all the systems that need the master data.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Warehousing Architecture							
Spread marts & Management Reporting Spread marts are spreadsheets or desktop databases that function as surrogate data marts. Management Reporting generate a standard set of static reports.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Data Marts A data mart is a shared, analytic structure that generally supports a single application area, business process, or department	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Data Warehouse Interactive Reporting and Analysis. users can now submit queries across functional boundaries, such as finance and operations, and gain new insights	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Enterprise Data Warehouse A flexible business intelligence layer finishes the job by integrating data in the EDW with external data that is impractical to load into the EDW for one reason or another	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Analytical Services The data warehouse and analytic server fade into the background becoming critical infrastructure that no one thinks about until it stops working due to an outage e.g. interactive extranets, web Services, decision engines and so forth.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Analytical							
Analytically Impaired In this stage, the company has some data and management interest in analytics.	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Localized Analytics Functional management builds analytics momentum and executives' interest through applications of basic analytics	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Analytical Aspirations Executives commit to analytics by aligning resources and setting a timetable to build a broad analytical capability	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
Analytical Company Enterprise wide analytics capability under	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐

development; top executives view analytic capability as a corporate priority.							
Analytical Competitor The company routinely reaps benefits of its enterprise wide analytics capability and focuses on continuous analytics review.	**1** ☐	**2** ☐	**3** ☐	**4** ☐	**5** ☐	**6** ☐	**7** ☐
Any Other Critical Factors							
	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐
	1 ☐	2 ☐	3 ☐	4 ☐	5 ☐	6 ☐	7 ☐