Governance Structures for Engineering and Infrastructure Asset Management

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Abstract--**Engineering asset lifecycle management is data driven. Asset lifecycle processes generate, process, and analyse enormous amount of data on daily basis. Asset lifecycle management can be viewed as a combination of data based informed decisions associated with strategic, planning, and operational levels of the organization. Realization of such a view of asset lifecycle requires appropriate quality, standardized, and interoperable data that provides the strategic fit between asset lifecycle processes and their enabling technologies. However, this data needs governance policies in place to ensure that it is managed and handled in a way that provides optimum value to the entire organsiation. This paper sketches out a framework for asset lifecycle management data governance, which highlights the roles and accountabilities related to asset lifecycle information management. The framework describes how common business data and metrics should be defined, propagated, owned and enforced throughout the organization, thereby allowing for better quality and faster decision making, business intelligence reporting, cost reductions, compliance, and better controls of business processes.**

I. INTRODUCTION

Quality, availability, and usefulness of data have a central role in creating a competitive and responsive organisation. Management, continuous exploitation, and enhancing value of data are, therefore, at the forefront of any CIOs (Chief Information Officer) agenda. Data Governance provides the way of managing data, and assigns accountability for management of data assets; providing the processes, policies, standards, technologies and people for management of data; the means by which organization ensures its data quality; and, assign roles and responsibilities to the people for managing data. Data governance is a quality control discipline for assessing, managing, using, improving, monitoring, maintaining, and protecting organizational information. It, thus, becomes a system of decision rights and accountabilities for information-related processes, executed according to agreed-upon models, which describe who can take what actions with what information, and when, under what circumstances, using what methods [12]. In essence data governance ensures that data can be trusted and that people can be made accountable for any adverse event that happens because of low data quality. It is about putting people in charge of fixing and preventing issues with data so that the enterprise can become more efficient.

Contemporary business organisations are increasingly moving towards data governance, a paradigm shift that is critical in achieving corporate goals through close collaboration between the CEO (Chief Executive Officer), CIO, and CTO (Chief Technology Officer). Thus, the scope of data governance discipline, which emerged from data quality and management practices, is continuously evolving and aims at creating responsive data enabled infrastructure to deliver the current and future data needs of the business in a controlled manner. Data governance supports the business to align its data/information needs and enabling infrastructure with its operating model. As a result of this strategic alignment the organisation ensures that the business not only meets its strategic goals but that its data resources become a cohesive component of its operations. Emphasis of data governance, however, is on data/information management practices to control and manage business processes, organisational risks, and operational disturbances, by proactively aligning the continually changing strategic business data needs with the evolving use of information technologies in the organisation. It includes planning and organizing; acquiring, processing, and managing; delivering and supporting; and monitoring of data for strategic business management. This paper presents a governance framework for data relating to asset lifecycle. It starts with a discussion on the role of information in enabling an engineering asset lifecycle. The paper then develops the case of data governance, followed by a data governance framework for asset lifecycle management. This framework is of particular interest to large sized public sector organizations that own, operate, and manage assets and are interested in developing an integrated and information enabled view of asset lifecycle. It should also be noted that this paper uses the terms data and information interchangeably.

II. ROLE OF INFORMATION IN ENGINEERING ASSET MANAGEMENT

The term asset in engineering organizations is defined as the physical component of a manufacturing, production or service facility, which has value, enables services to be provided, and has an economic life greater than twelve months [7]. Some examples include, manufacturing plants, roads, bridges, railway carriages, aircrafts, water pumps, and oil and gas rigs. Core asset management processes are derived from the asset management strategy and are enabled through various operating plans and procedures. These include asset design, acquisition, construction, and commissioning; operation; maintenance; refurbishment; decommissioning; and replacement. Core asset management consists of three cycles, i.e. primary asset management cycle, learning and change cycle, and renewal cycle (fig. 1).

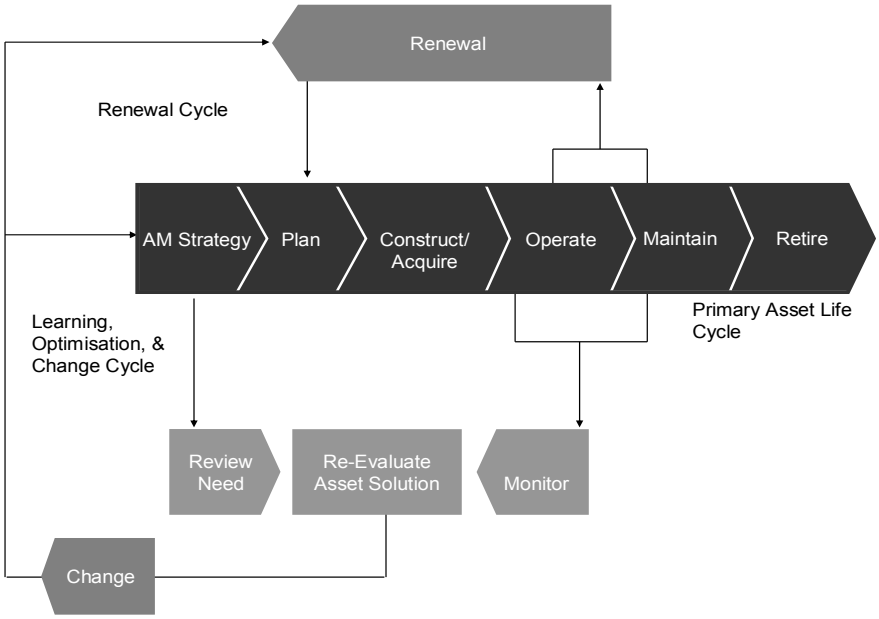

Fig. 1: Asset Management Cycles
(Source [4])

Primary asset management cycle is derived from the asset management strategy and includes asset construction and commissioning; operation; maintenance; and retirements stages. The fig.1 explains how learning and optimisation, and renewal cycles are initiated and what impact they have on the primary asset lifecycle. The learning, optimisation, and change cycle is aimed at change, enhancement, and maturity of an asset solution in response to factors such as asset need redefinition, technology refresh, environmental and regulatory concerns, and economic tradeoffs. However, the crucial factor in this cycle is the ability of the organisation to continuously evaluate primary asset lifecycle achievements and compare them with the strategic business objectives. This gap analysis provides learnings on effectiveness of the existing asset solution in meeting the strategic needs of the organisation. The objectives of this exercise are, firstly, to identify enhancements in asset solution design, and secondly (if the first is not possible) to provide alternatives for asset renewal. In doing so, the learning, optimisation, and change cycle calls for redefinition of asset strategy, whereas the renewal cycle informs and necessitates adjustment of asset management plan. It is clear that asset lifecycle is information intensive; however information requirements of lifecycle management processes are prone to change with the continuously changing operational and competitive environment in which the assets operate. Therefore, the ability of an organization to understand these changes contributes to its responsiveness to internal and external challenges, as well as its capacity to improve and enhance reliability of asset operations. The real value of information systems for asset management comes from how effectively information systems capture, retrieve, exchange, and manipulate data to enable lifecycle processes as well as provide quality decision support. Asset managing organisations, therefore, need to treat data as an asset of the organization, and put data governance policies in place to ensure that it is handled and managed properly. Data governance allows asset managing organisations to take ownership of data, gain optimum value from it, assign responsibility and authority related to data functions and decision making, implement accountability measures for misuse and any detrimental consequences of low quality of data, and continuously monitor data for any anomalies and take corrective action.

III. DATA GOVERNANCE

Data governance represents the enterprise policies or strategies that define the purpose for collecting data and governing the ownership and intended use of data [3]. Data governance is top driven and is a critical component of a CIO's agenda. It is, however, a subset of IT governance where many models and approaches remain the same though a more limited domain is governed – only activities and issues relating to data [1]. Ironically, data governance is largely absent from many pieces of literature and frameworks on IT governance. As data is used as a foundation of those functions, if it is not kept 'clean' and the overall data quality is reduced, it ends up affecting the bottom line of the organization. This negative effect on the bottom line is becoming more and more evident, for example, in North America over $600 billion in lost revenue has been attributed to the data quality among businesses [8]. At the same time, growing emphasis on information exploitation and business intelligence for sustainability and profitability is also forcing businesses to adopt data governance. For example, a survey

of two hundred and fifty seven organizations by reference [14] found that the main driver for the implementation of data governance was to support business intelligence initiatives. However, accountability is the main function of data governance and often starts with top management of the organization. From this top layer, stewardship is assigned to individuals or groups. Data stewardship helps with compliance with data policies set in place from data governance, ensuring that data is used for its intended purpose [3]. Stewardship is often assigned to the managers or committees that are subject matter experts. In asset management industry, data stewards are particularly important, where error in data can cause major problems for asset operators, maintainers, as well as the service that the assets enable. Asset managing organizations particularly require critical error checking and analysis of all data, as any discrepancies or problems may affect the reputation of the organization and possibly be threatening for the economy of the country ([6]). Data governance, however, is not just about improving quality of data alone. It is about managing the overall intellectual capital of the organization so as to enable a continuous improvement based learning progression. Therefore, data governance includes technical, organisational, as well as people aspects related to optimum utilisation of information systems to produce, maintain, manage, and use data for the internal and external growth and maturity of the organisation.

Selection and implementation of a data governance framework is a major issue for business organisations as the choice will also have an effect on the information technology operations in the organisation. Ultimately the choice of a data governance framework requires an analysis of the organisation's data resources, their enabling infrastructure, and the processes and practices that control and manage the data lifecycle. There are a number of data governance frameworks in action in industry. At the higher level, each of these frameworks aims to align strategic business considerations with information, mitigate and manage risks, add value to the organisation by effective management of organisation value. However, in their mechanics each one is different from the other. The followings sections provide a discussion of the most commonly adopted data governance formworks.

IV. APPROACHES TO DATA GOVERNANCE

A. Dataflux Data Governance Framework

Dataflux data governance maturity framework aims to guide the organisation through ad-hoc undisciplined data governance imitative to an integrated and value adding established data governance. The framework, as illustrated in fig. 2, proposes progress towards a unified enterprise view of data governance through four distinct stages. These stages include, undisciplined, reactive, proactive, and governed. The framework highlights consolidation and integration of information resources.

It starts with consolidation of individual data projects (such as sales force enablement) and then aims to integrate information from these disparate functions. Thus, the four stages of this framework are scaled, and migration or up-gradation from one level to the next one does not happen automatically. Each stage requires appropriate technical, organisational, and people resources, which collectively aim to mitigate risks posed to the business from information and data mismanagement. The gulf between the second and third stage highlights major cultural, managerial, and organisational changes required to move from a reactive mode to proactive mode.

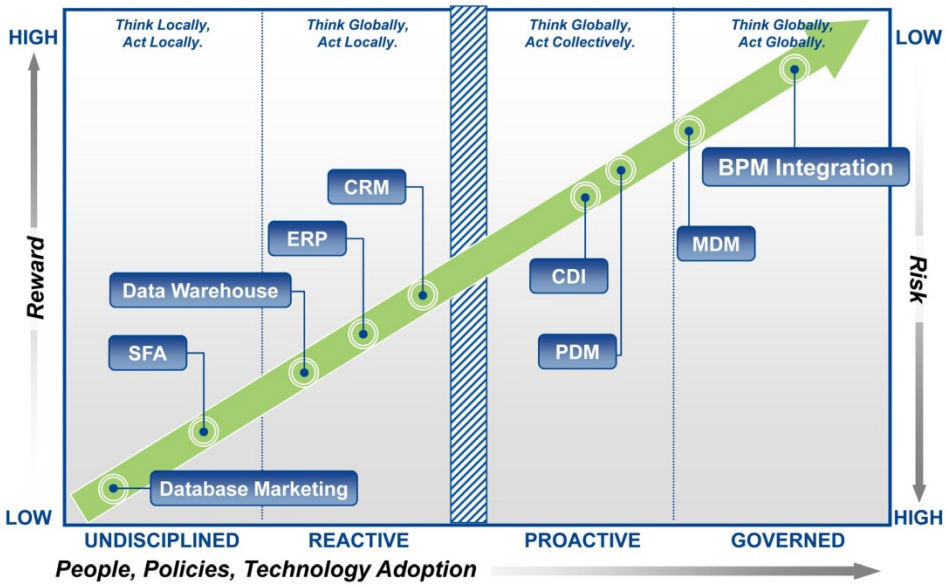

Fig. 2: DataFlux Data Governance Maturity Framework
(Source [2])

The framework takes the organisation from non-integrated disparate solutions to a fully integrated and continuously improving information and information enabling technical as well as non technical infrastructure. It emphasises information managers to create a strategic vision for data governance and put in place polices, processes, and enabling technologies to correct and consolidate data, leading to improved business results. In this quest, the framework takes the organisation from simple applications to complex integrated systems like enterprise resource planning, customer relationship management, through customer data integration (CDI) and product data management (PDM) solutions across various business functions. The framework thus takes an incremental approach, whereby it matures data governance in the organisation by starting from managing data and information locally and expanding the scope and span of data governance expertise to the entire organisation. In doing so, management can plan how the organisation is going to move to a higher level, draw upon the expertise and competencies developed at the existing level, and make appropriate changes (technical, organisational, cultural, and people) to facilitate the transition process. The framework, however, is heavily slanted towards data quality and data integration capabilities as the core components. Thus, it forces the organisation to conform to specific technology architectures (such as service oriented architecture) to couple data management processes to operational applications. Nevertheless, the framework requires management of four critical dimensions to achieve data governance maturity. These include,

a. People. Identification of stakeholders who are involved at each stage of maturity, what must they do, and how they interact with each other to ensure success of the tasks at each stage.
b. Process. What business processes must be executed at each stage of maturity, and how these processes influence and are influenced by the execution of each process. This is based on how information is shared among stakeholders and applications to ensure smooth execution of each process.
c. Technology. What technologies are necessary to facilitate the organisation's path to data governance maturity? This involves mapping information requirements on to technology, managing technology lifecycle, and technology succession plans due to end of need or technology refresh.
d. Risks and Rewards. What information risks are posed to the organisation at each stage of maturity? What corporate risks can materialise due to information risks? What tradeoffs contribute or risk management and moving from one level to the next higher level?

B. Gartner's Data Governance Framework

Gartner's information governance maturity framework (illustrated in fig. 3) is more of an information management framework than a governance framework. The activities involved in this framework are focused on information lifecycle and value management, rather than proposing governance mechanisms for information as well as information lifecycle related technical infrastructure. The framework, however, has six stages, i.e. unaware, aware, reactive, proactive, managed, and effective. This framework is aimed at structuring, securing, and improving the accuracy and integrity of enterprise information. However, it needs to be highlighted that the framework takes a few things for granted, for example, that the organisation has established enterprise architecture, consequently meaning that the organisation conforms to an information model.

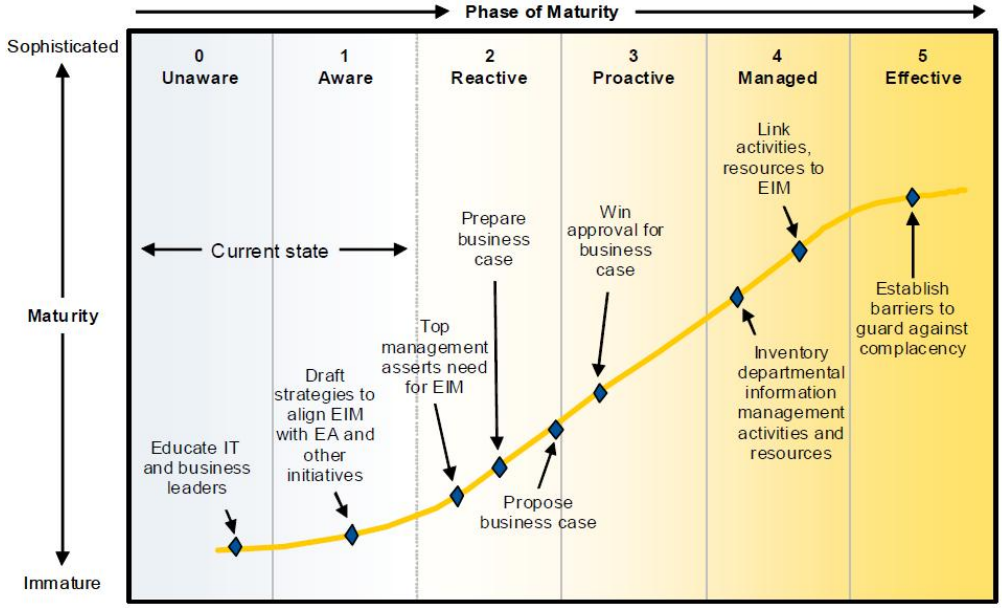

Fig. 3: Gartner Enterprise Information Governance Maturity Framework
(Source [11])

This framework acknowledges that data governance is not a one-off activity; in fact it is a continuous process of evolution that takes the organisation from one step to a higher one over the period of time. It assumes that organisations always start from the elementary steps, and move along the continuum of unawareness to a fully effective program of data governance. It also assumes that most organisations are in the early stages of maturity, and the model works best for them. It, therefore, requires the organisation to follow linear and incremental path to maturity without skipping any step. The framework suggest that if any step is skipped, then the organisation is exposed to various weaknesses that lead to future failure of the organisation to derive value from the data governance initiative. In other words, it suggests that following each activity, process, and step is essential for developing an over arching maturity of the data governance capability. The framework is strongly focused around regulatory requirements and standards. It, therefore, presents a mechanistic approach to data governance with predetermined and well defined and assumed cause and effect relationship between various steps and embedded activities.

C. IBM Data Governance Framework

IBM has been quiet proactive with its data governance. It has formed its own exclusive data governance to plan, execute, manage, and improve its data governance initiatives. In this regard IBM has developed a data governance maturity model (fig. 4) based on software engineering institute's Capability Maturity Model (CMM). This framework represents a mix of administrative and operational activities in eleven domains within four major categories, i.e., outcomes, enablers, core disciplines, and supporting disciplines.

This framework is quite comprehensive and the level of bureaucratic detail involved in this framework makes it difficult for small to medium sized enterprises to adopt it. It suggests multiple levels of control, and is, therefore, quite heavy on accountability.

D. Data Management Association International (DAMA) Framework

Data governance is a monolithic whole of a number of different dimensions relating to data management. These dimensions allow for elementary dimensions of data management like reference data development to more advanced and elaborate dimensions like data quality, architecture, and business intelligence management. Fig. 5 describes the broader scope of data governance dimensions relating to planning, controlling and delivering data and information assets.

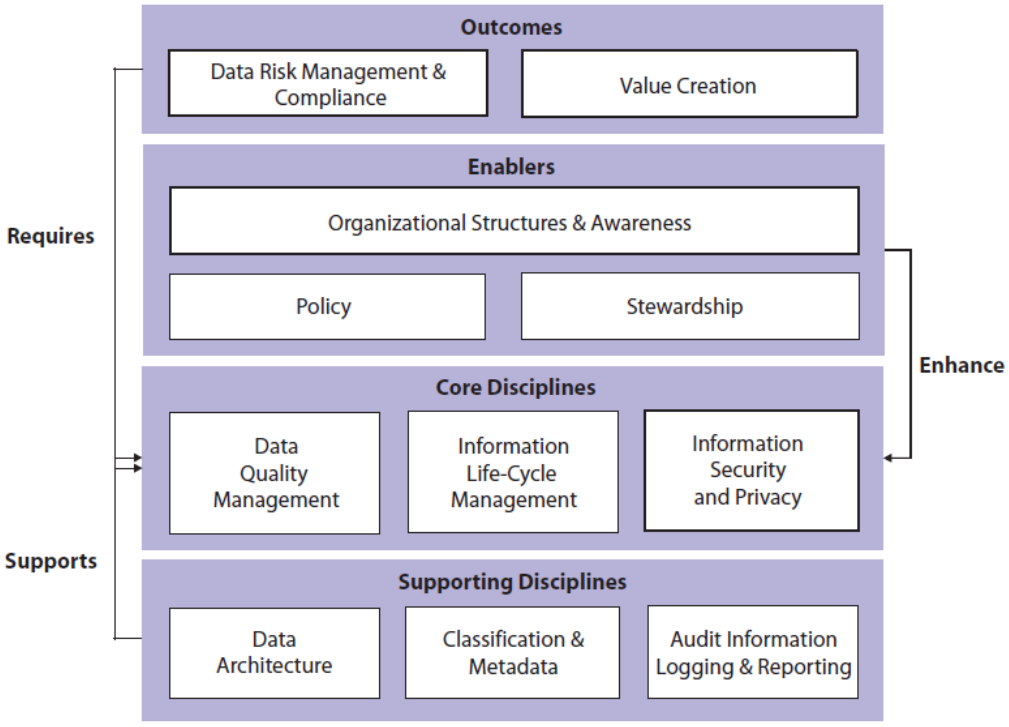

Fig. 4: IBM Data Governance Domains
(Source [13])

Fig. 5: DAMA Data Governance Framework
(Source [10])

This framework provides a comprehensive foundation for an all encompassing data governance initiative. It presents nine domains where data makes significant impact on the planning, execution, risk management, and maintenance of the business. Table 1 explains these domains and describes an explanation of each of these domains.

Other data governance initiatives significantly applied in the industry includes frameworks and models such as Knowledge Logistics data governance framework, MDM Institute data governance framework, and Oracle data governance framework. However, there is an open source delivery framework for enterprise information management, i.e. Method for an Integrated Knowledge Environment (MIKE 2.0), which is gaining significant attention in industry and consultancy.

TABLE 1: DAMA DATA GOVERNANCE DOMAINS
(Source [10])

Domain	Description
Data architecture management	Development and maintenance of overall data architecture of the organization.
Data security management	Maintaining integrity of data by supporting activities those ensure privacy and confidentiality of data in an organization.
Reference & master data management	Providing the reference for data and ensuring consistency of data values with real data values.
Metadata management	Supporting activities that ensure easy access to high quality data
Data quality management	Planning and implementation of techniques and processes that makes data fit for use and ensures its high quality.
Data warehousing and business intelligence management	Planning, implementation and control processes to provide decision support data and support knowledge workers engaged in reporting, query and analysis.
Document and content management	Maintaining record of documents and contents (unstructured data) data and ensures that proper documentation, videos, graphics and images have been stored to support the integrity of data with real data values.
Data development	Providing solutions for data focused activities within system development lifecycle. It includes the modelling, analysis, design, implementation and testing of data in real time.
Database operations management	Controlling databases operations and providing support for data assets across the data lifecycle.

Although it is a not a data governance platform, yet it covers a few areas/domains for data governance. It provides a methodology that can be applied across different information management related projects within an organization. MIKE2.0 [9] was initially developed for managing structured information, however, through continuous evolution it now caters for development of structured, semi-structured, as well as unstructured data.

V. DATA GOVERNANCE FOR ASSET MANAGEMENT

It has been established in earlier sections that asset managing organizations need to have a long term vision of how they generate, process, and manage data to enable a continuous improvement regime for asset solution as well as lifecycle support. Therefore, asset lifecycle management needs to be data/learnings focused, such that each lifecycle stage draws from and contributes to it to create a learning based integrated view of asset lifecycle. Information enabled integrated asset lifecycle management, thus, implies that information requirements of asset management should dictate planning, execution, and management of asset lifecycle. A data governance model for asset management is illustrated in Fig. 6. This model is divides asset lifecycle into seven perspectives, i.e. competitiveness, design, operations, support, stakeholders, lifecycle efficiency, and learning perspective. It embeds aspects like data quality, integration, standardization, interoperability, and risk management into the model through the connections between different perspectives.

The arrow in the middle signifies that this model enables generative learning based continuous improvement cycle in the organisation. From top down, the model guides data governance policies and initiatives in mapping the organization's competitive priorities into asset design and reliability support infrastructure. The model guides data governance initiatives through five further perspectives before informing the competitive priorities of the asset managing organization. In doing so, the model guides how data governance functions should be implemented, and at the same time can also assess the effectiveness of existing data governance functions. It thus shapes the role of data as strategic translator as well as strategic enabler of asset lifecycle management and enables generative learning. Instead of just being open ended and laying down guidelines for implementing data governance initiatives, the model has inbuilt assessment that provides a gap analysis of the desired versus actual state of the maturity of data governance initiatives in the organization.

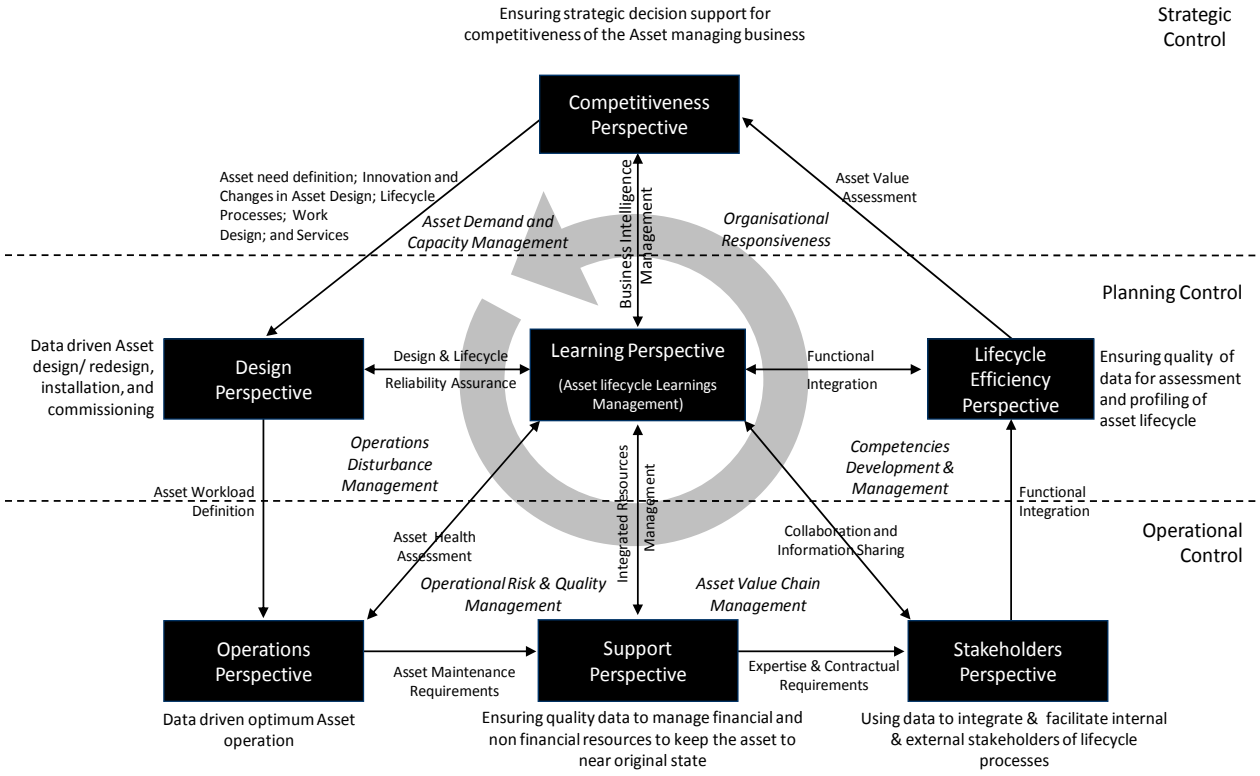

Fig. 6: Data Governance Model for Asset Management
Source (adopted and modified from [5])

Fig. 7 illustrates the approach to data governance implementation in the organisation. First and foremost the organisation needs to the business processes within each asset management domain perspective of the model described in the model in fig. 6 above. Next step is to develop baseline data governance guideline, which could be used as targets for data governance initiatives within the organisation. The data governance areas that the authors recommend for asset management have been adopted from reference [10], i.e. data architecture management; reference & master data management; metadata management; data quality management; database operations management; data warehousing and business intelligence management; document and content management; data development; and data security management. These data governance areas are then applied to each of the business processes identified for the asset management domain perspectives.

Table 2 presents a worksheet template for applying data governance areas to the business processes identified for the asset management domain perspectives. The template should be use to record data governance activities within each of the data governance areas, as well as the job descriptions and responsibilities related these activities and the technologies to be used to support these activities. The deliverables from each of the data governance areas should be recorded, so that these could be audited periodically for continuous improvement of the overall data governance plan of the organization.

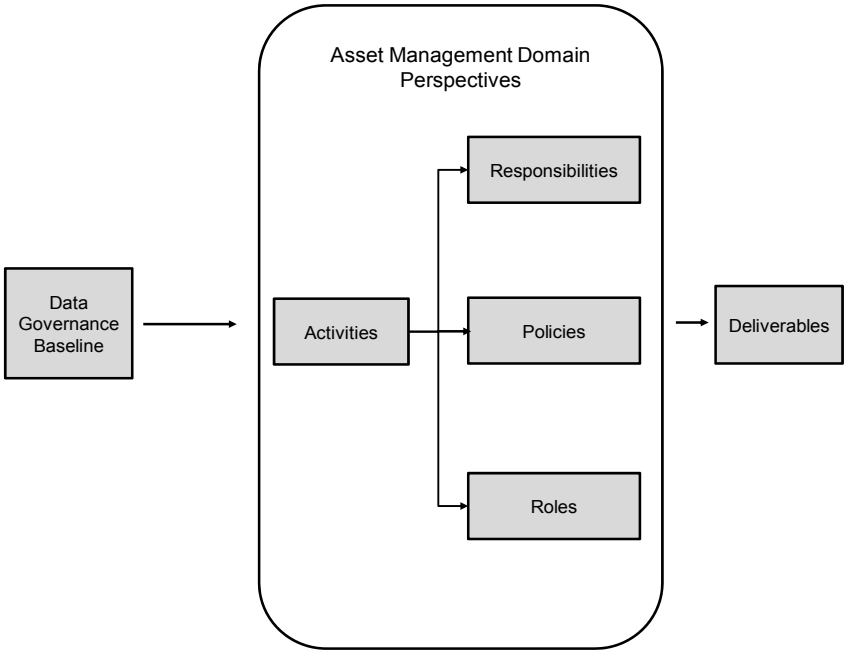

Fig. 7: Framework for Data Governance Implementation

TABLE 2: DATA GOVERNANCE WORKSHEET

	Domain Perspective Process	**Data Governance Activities**	**Roles & Responsibilities**	**Technology**	**Deliverables**
Data Development					
Database Operations Management					
Data Security Management					
Reference & Master Data Management					
Data Warehousing & Business Intelligence Management					
Document & Content Management					
Metadata Management					
Data Quality Management					
Data Architecture Management					

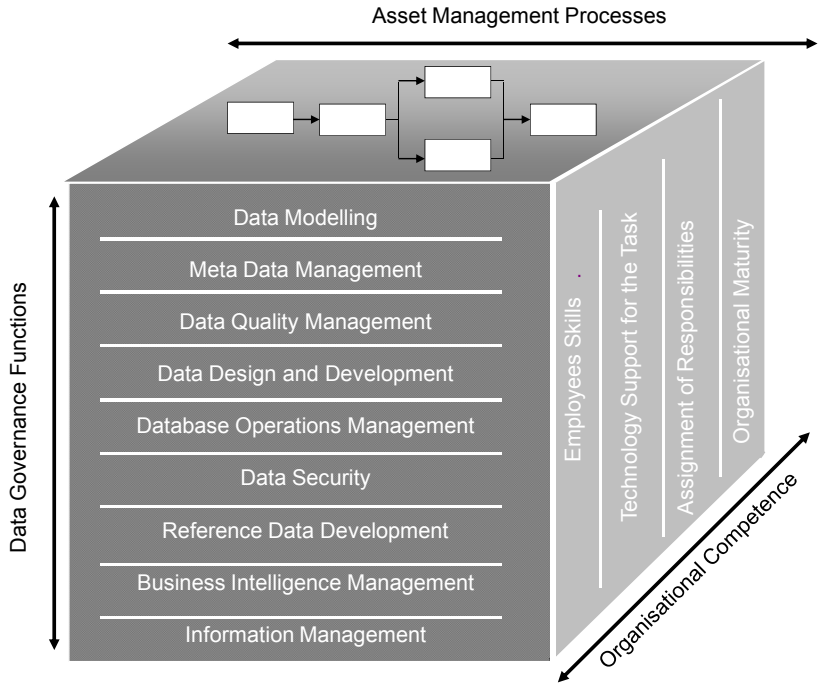

Fig. 8: Data Governance Cube

Introduction, sustenance, and maturity of data governance in asset management depend upon three dimensions, i.e. asset lifecycle processes; functional elements of data governance; and the critical factors that contribute to organizational competence that facilitate data governance. Therefore, it is essential to evaluate the effectiveness of data governance initiatives. Fig. 8 illustrates the data governance cube to be applied to each of the seven perspectives of the model described in fig. 3. For each process, data governance functions will be assessed completed according to the different dimensions of organizational competence. Here, asset managing organizations could adopt any scale of assessment that suits their environment. Any psychometric scale like Likert scale would be useful. When these assessments are compared with the data governance baselines, the result would be a gap analysis between the existing and optimum state of data governance in the organization. This gap analysis could work as the roadmap for sustenance, maturity, and continuous improvement of data governance functions and related organizational resources.

V. CONCLUSION

Data governance is an important topic for any organization that acknowledges the importance of their business data as a foundation to their success. It is an area of corporate management that looks at decision making and authority for data related matters. This paper has presented a case of data governance for asset lifecycle management by highlighting how is it relevant to asset management, and how it could be implemented. This paper highlights that technology alone cannot provide data governance; therefore, it is important to develop skills, pocess competemceis, and operational matuirty to strengthen secuity and quality of organsiational data. In the next step of this research, the developed model and franework will be validated in three Australian asset magiaging organsiations.

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