DATA GOVERNANCE – DEFINING ACCOUNTABILITIES FOR DATA QUALITY MANAGEMENT

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Abstract

Enterprises need data quality management (DQM) to respond to strategic and operational challenges demanding high-quality corporate data. Hitherto, companies have assigned accountabilities for DQM mostly to IT departments. They have thereby ignored the organisational issues that are critical to the success of DQM. With data governance, however, companies implement corporate-wide accountabilities for DQM that encompass professionals from business and IT. This paper proposes a contingency approach to data governance. It outlines a data governance model based on IT governance research. The model comprises a first set of data quality roles, decision areas and responsibilities. The data governance model documents the data quality roles and their type of interaction with DQM activities. In addition, the paper identifies contingencies and their impact on the model configuration. Companies can implement their company-specific data governance model based on these findings.

Key Words: Data Governance, Data Quality Management, Data Governance Model, IT Governance, Contingency Theory

1 INTRODUCTION

Today, companies are forced to continuously adapt their business models. Global presence requires harmonised business processes across different continents, customers ask for individualised products, and service offerings must be industrialised (Borzo 2005). This certainly has an impact on the business process architecture and the IT strategy of organisations. Ultimately, however, data of high quality is a prerequisite for fulfilling those changing business requirements.

In addition to such strategic factors, there are more operational domains which directly rely on high-quality corporate data:

- *Business Networking*. Many industries are characterised by decreasing ranges of manufacture. Cooperating and communicating with business partners along the value chain requires high-quality data. For example, in order to automatically process orders via EDI, product information have to be aligned between business partners, which leads to higher requirements on data quality (Vermeer 2000).
- *Customer management.* Providing superior customer service and making customer management profitable requires a complete value chain from data collection, through data quality management and marketing performance metrics to knowledge management (Crié & Micheaux 2006). CRM systems, data warehouses and customer data integration support daily customer operations if they assemble customer data from several sources in high quality (Reid & Catterall 2005).
- *Decision-making and business intelligence.* Decision-making today is characterised by larger volumes of data at different levels of granularity, high frequency and a large variety of decision tasks, and multiple stakeholders. Efficient, proactive and systematic data quality management supports decision-makers in this dynamic environment (Shankaranarayan & Ziad & Wang 2003, Price & Shanks 2005).
- *Regulatory compliance.* Regulatory compliance is one of the major business drivers for data quality improvement initiatives. High-quality data enables companies to attest the accuracy of financial statements and to provide other compliance-oriented deliverables (Friedman 2006).

Today, responsibility for improving and managing corporate data is often assigned to IT departments (Friedman 2006). Findings of a recent survey among data management professionals indicate that data governance is rare in today's enterprises (Russom 2006). Only 8% of respondents had deployed a data governance initiative, 17% were in the design or implementation phase. Also, many companies try to cope with data quality issues by simply implementing a data management or data warehouse system. Instead, an integrated data quality management (DQM) that combines business-driven and technical perspectives is needed. Data governance is a concept to implement corporate-wide accountabilities for data quality management that involve both business and IT.

Data Governance specifies the framework for decision rights and accountabilities as part of data quality management. More precisely, data governance defines roles and assigns responsibilities for decision-areas to these roles. Data governance sets-up organisation-wide guidelines and standards for DQM and assures compliance to corporate strategy and laws governing data.

Researchers proposed approaches to DQM to help companies improving corporate data quality (e.g. Wang & Lee & Pipino & Strong 1998, English 1999, Nohr 2001, Eppler 2006). They deal with the accountability aspect within DQM by describing data quality roles and their responsibilities (Redman 1996, English 1999). In addition, some authors described employee's skills necessary for filling these roles (Dyché & Levy 2006, pp. 167-173). Research on IT governance suggests that the distribution of roles to responsibilities in IT management differs between companies based on contingencies, such as corporate governance mode or firm size (Sambamurthy & Zmud 1999, Weill 2004, Weill & Ross 2005). A similar analysis for data quality management is missing. Previous research presumes data governance as a universal approach – one that fits all enterprises alike. This might be the reason, why companies still find it difficult to set-up and maintain organisational structures to assure and sustain high-quality data throughout the enterprise.

We use IT governance as reference discipline for data governance. Basically, both disciplines aim at answering the same question: How does data / IT governance enable data quality / IT to deliver enterprise value? (cp. Weill & Ross 2005) We propose that – similar to IT governance – contingencies affect data governance and that a data governance configuration is specific to a given company. A data governance model that is composed of roles, decision-areas and responsibilities can be used to outline a specific data governance configuration. From the field of IT governance, we identify a first set of contingencies and their impact to that model. In this paper, we focus on the accountability aspect of data governance, disregarding its guidelines and compliance facet.

We contribute to data quality management research by advancing the accountability aspect of data governance. In contrast to previous research, we propose a contingency approach to decision-making frameworks within DQM. The data governance model outlines the three components of such a framework, namely roles, decision-areas and responsibilities. For the components, we identify typical data quality roles and decision areas, and propose a method to assign responsibilities. We propose a first set of contingencies and demonstrate their impact on the data governance model.

Our approach respects that each company needs a specific data governance configuration contingent to a set of influencing factors or contingencies. A data governance model helps companies to structure their data quality accountabilities. Based on our proposed roles, decision-areas and responsibilities, companies can outline their individual data governance configuration. The contingencies and their impact on the model help them to find a configuration that best fit their company.

The remainder of the paper is structured as follows: Section 2 introduces related work on data quality and data quality management, data governance, IT governance archetypes, and IT governance contingencies. Section 3 outlines the idea and the structure of the data governance model. It proposes a first set of data governance roles, decision areas, responsibilities and contingencies. The last section summarises this paper and discusses its contribution to data quality management.

2 BACKGROUND

2.1 Data, Data Quality and Data Quality Management

The term data is often distinguished from information by referring to data as “raw” or simple facts and to information as data put in a context or data that has been processed (Huang & Lee & Wang 1999, p. 13, Pierce 2005, Price & Shanks 2005). In line with most data or information quality publications, we use the terms data and information interchangeably throughout the paper.

Data or information quality is defined based on two consentient aspects: First, the dependence of perceived quality from the user’s needs; second, the so-called “fitness for use”, which is the ability of satisfying the requirements of intended use in a specific situation (Redman 2000, pp. 73-74, Olson 2003, p. 24). One common denominator of these definitions is that DQ is considered a multi-facet construct, consisting of a set of DQ attributes (so-called data quality dimensions) requiring consumer assessment (Wang & Strong 1996, p. 6). Examples for these dimensions are accuracy, completeness, consistency, relevancy, and timeliness.

Data management comprises all organisational, methodical, conceptual and technical tasks related to managing data as an asset. We refer to data quality management as quality-oriented data management, i.e., data management focussing on collection, organisation, storage, processing, and presentation of high-quality data. Total Data Quality Management (TDQM) is the best known approach to DQM (Wang 1998, Wang et al. 1998, Huang et al. 1999). The key message of TDQM is to manage information as a product by following four simple principles. The TDQM methodology is built around the lifecycle of continuously defining, measuring, analysing, and improving information quality. The only role accountable in TDQM is the information product manager, which ensures that relevant, high-quality information products are delivered to information consumers.

2.2 Data Governance

So far, no academic definitions of data governance exist. Looking at literature on IT governance, data governance can be defined as *specifying the framework for decision rights and accountabilities to encourage desirable behaviour in the use of data* (cp. Weill 2004). This definition comprises three elements. First, roles that are accountable for and manage data have to be appointed. This part is often referred to as data stewardship (English 1999, p. 402, Russom 2006). Second, the decision areas need to be defined. With respect to data quality management, decision areas include establishing a data quality strategy, creating standards and policies, defining data management processes, and setting up a data architecture etc. Finally, decision practices have to be aligned with corporate governance principles. To promote a desirable behaviour, data governance develops and implements corporate-wide data policies, guidelines and standards that are consistent with the organisation’s mission, strategy, values, norms and culture (cp. Weill 2004).

However, it is important to expose that data governance is not a subset of IT governance as argued by Dyché and Levy (2006). As outlined above, data quality management involves both business and IT-related perspectives. Hence, we argue that data governance and IT governance are coequal and both have to follow corporate governance principles. Furthermore, data governance should be clearly distinguished from data quality management (Sambamurthy & Zmud 1999, Weill 2004, Dyché & Levy 2006, Russom 2006): data governance provides a framework for management decisions; actual “day-to-day” decision-making is data quality management. Figure 1 illustrates the relationships between the terms explained.

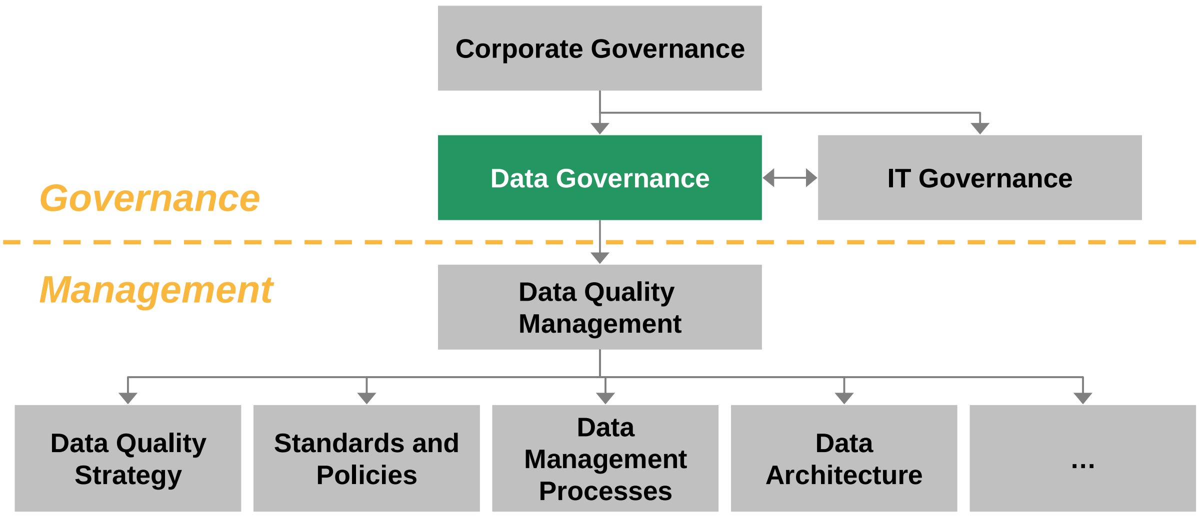

Figure 1. Terms in Governance and Management

Academic research on data governance is in its infancy. Apart from a few DQM approaches dealing with accountabilities (Redman 1996, pp. 273-288, English 1999, pp. 401-419), an elaborate analysis of the interaction of roles and responsibilities and the design of decision-making structures is missing. Therefore, our research also incorporates the following data governance sources from consultants and practitioners. Dember (2006) and IBM (2006) propose Data Governance Maturity Models. The models consist of disciplines for successful data governance implementations and maturity, such as stewardship culture, strategic governance, and risk management. The study by Russom (2006) illustrates the status-quo of data governance and data quality management. In addition, it explains cornerstones of both topics and expresses practical recommendations. In their book on customer data integration, Dyché and Levy devote a chapter to data governance and stewardship (Dyché & Levy 2006, pp. 145-182). They argue that a clear data governance framework is fundamental for CDI implementation.

However, all approaches postulate a universal approach to data governance. They describe accountabilities as “one best way” to organise. Following the contingency theory of organisations (e.g. Donaldson 2001), maximum performance in data quality management results from appropriate decision-making structures. Appropriate means, a data governance configuration has to “fit” an individual company’s characteristics. The characteristics are called contingencies. From an academic viewpoint it is interesting to find out what are the contingencies and how do they affect data governance configuration. The next two sections describe similar research in IT governance.

2.3 IT Governance Archetypes

This research on data governance was stimulated by findings in IT governance from Weill (2004). Weill analysed IT governance in more than 250 enterprises and identified six IT governance patterns. The “archetypes” define how enterprises assign decision and input rights to govern key IT decision areas. For Weill, governance is about “systematically determining who makes each type of decision (a decision right), who has input to a decision (an input right), and how these people (or groups) are held accountable for their role.” (Weill 2004, p. 3) IT governance focuses on five major decisions areas, such as IT Principles, IT Architecture, and Business Application Needs. Per archetype, he defines the combinations of people who have decision or input rights per key IT decision. Table 1 depicts a summary of the IT Governance Archetypes.

Decision Rights or Input Rights for a particular IT Decision held by:		CxO Level Execs	Corp. IT and / or Business Unit IT	Business Unit Leaders or Process Owners
Business Monarchy	A group of, or individual, business executives (i.e., CxOs). Includes committees comprised of senior business executives (may include CIO). Excludes IT executives acting independently.	✓		
IT Monarchy	Individuals or groups of IT executives.		✓	
Feudal	Business unit leaders, key process owners or their delegates.			✓
Federal	C-level executives and at least one other business group (e.g., CxO and BU leaders) - IT executives may be an additional participant. Equivalent to a country and its states working together.	✓	✓	✓
		✓		✓
IT Duopoly	IT executives and one other group (e.g., CxO or BU leaders).	✓	✓	
			✓	✓
Anarchy	Each individual user.			

Table 1. IT Governance Archetypes (Weill 2004, p. 5)

The IT governance archetypes indicate that there are three elements that compose an IT governance model: roles, major decisions, and assignment of accountabilities. In addition, to provide enterprises with guidance to choose a pattern that fit their organisational structure and market environment, contingencies need to be identified. We translate the concept of archetypes and their three elements into the data governance model. The data governance model is comprised of roles in data quality management, decision areas or main tasks, and responsibilities, i.e. which role is in what way accountable for a certain task.

2.4 IT Governance Contingencies

The effectiveness of a company's IT governance approach depends on how well it fits the companies' individual situation (Weill 2004, Weill & Ross 2005). Contingency theory of organisational design has outlined similar dependencies (Lawrence & Lorsch 1967, Donaldson 2001, Keats & O'Neill 2001): the relationship between some characteristic of an organisation and its organisational effectiveness is determined by contingencies. These contingencies or contingency factors can be found within and outside the organisation.

For IT governance, Weill and Ross (2005) analysed the contingency "performance". They found that companies focussing on efficient operations and high profitability tend to centralised IT governance approaches (e.g. IT Monarchy and Federal). Fast-growing companies focus on innovation and time to market use a decentralised approach to IT governance (e.g. Feudal). Companies in between seek optimal asset utilisation. They tend to hybrid IT governance approaches (e.g. Federal and IT Duopoly).

In an earlier study, Sambamurthy and Zmud (1999) investigated multiple contingencies and their influence on the location of IT decision rights. They distinguished a centralised IT governance mode, i.e., corporate IS has the decision rights, and a decentralised IT governance mode, i.e., divisional IS and line management assume authority for IT decisions. Table 2 summarises the characteristics of the contingency factors and their influence on the locus of decision rights.

Category of forces	Contingency factor	Locus of decision rights	
		Corporate IS	Division
Corporate Governance	Overall governance mode	Centralized	Decentralized
	Firm size	Small	Large
Economies of scope	Diversification mode	Internal growth	Acquisition growth
	Diversification breadth	Related markets	Unrelated markets
	Exploitation strategy	Enterprise-wide consolidation of assets	Enterprise-wide line/IS partnerships
Absorptive capacities	Line IT knowledge	Low	High

Table 2. Contingency Factors Influencing the Locus of Authority of a Firm's IT decision making (cp. Sambamurthy & Zmud 1999, Table 2)

Weill (2004) named strategic and performance goals, organisational structure, governance experience, size and diversity, and industry and regional differences as contingent to IT governance. However, he did not specify how these factors influence the IT governance archetypes.

For our research we transfer the contingency theory to data governance and identify contingency factors to the data governance model.

3 A MODEL FOR DATA GOVERNANCE

3.1 Structure of the Data Governance Model

Following the IT governance archetypes, the data governance model is comprised of three components: roles, decision areas and responsibilities. The components are arranged in a matrix (cf. Figure 2). The columns of the matrix indicate the roles in DQM. The rows of the matrix identify the key decision areas and main activities. The cells of the matrix are filled with the responsibilities, i.e., they specify degrees of authority between roles and decision areas.

A company outlines its individual data governance configuration by defining data quality roles, responsibilities, and decision areas, and subsequently arranging the components in the model. This configuration is unique for each company. However, we argue that contingencies impact the outline of the model. Knowing the contingencies and their impact to the model, companies are provided with indications how to structure their data governance model. These indications are very valuable for companies since they need practical guidance on how to fill in the matrix. A data governance model that fit the contingencies will positively influence the performance of data quality management.

Indications for useful and necessary roles, possible decision areas and the impact of contingencies are given in the subsequent sections.

Roles / Decision Areas	Executive Sponsor	Data Quality Board	Chief Steward	Business Data Steward	Technical Data Steward	...
Plan data quality initiatives	A	R	C			
Establish a data quality review process	A	R	I			
Define data producing processes		A	R	C	C	
Define roles and responsibilities			...			
Establish policies, procedures and standards for data quality				...		
Create a business data dictionary		...				
Define information systems support						
...						

R – Responsible; A – Accountable; C – Consulted; I – Informed

Figure 2. Draft of a Data Governance Model

3.2 Data Quality Roles

To improve data quality and maintain high-quality corporate data a company requires specific data quality management roles and committees. Literature, studies and case studies on IT and Data Governance usually distinguish between three and five roles (IT Governance Institute 2003, Gonzalez-Mesa Hoffmann & Weill 2004, Swanton 2005, Marco & Smith 2006, Russom 2006, Smalltree 2006). Dyché and Levy (2006) and English (1999) describe roles that are more specialised – they distinguish twelve and nineteen roles. The analysis of these sources results in a set of four roles and one committee – the data quality board. They are depicted in Figure 3 and explained below. Business-driven and technical perspectives on data quality management are reflected in the distinction between business stewardship roles and technical (or information systems) stewardship roles (English 1999). Superior boards and chief roles consolidate both views.

The actual number of roles may vary from company to company. However, we think that the roles presented build a balanced and useful set when focussing on the strategic notion of data quality management. For example, a database administrator clearly has to assure "structural" integrity of data, but is also responsible for security, recoverability and performance of databases, which are less quality-oriented tasks (cp. English 1999, p. 412).

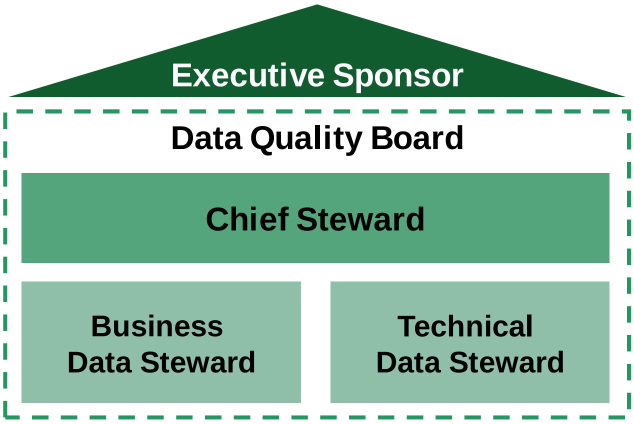

Figure 3. A First Set of Data Quality Roles

Executive Sponsor

Support from top management, which is crucial for corporate data quality initiatives, results from the executive sponsor. The executive sponsor is a member of the top management, such as the CEO, CFO or CIO. Besides supporting data quality initiatives and data governance, he provides sponsorship, strategic direction, funding, advocacy and oversight for data quality management.

Data Quality Board

The Data Quality Board defines the data governance framework for the whole enterprise. Its function is to define data quality roles, responsibilities and authority with support from the executive sponsor. In addition, the board sets top-down strategic goals and ensures that they are in line with the organisation's mission and objectives. More particularly, it develops and directs corporate-wide standards, rules, policies, processes, and guidelines to ensure the ongoing improvement of data quality. Furthermore, the board communicates with the executive management and provides mechanisms for coordination, communication, information sharing, prioritisation, and conflict resolution. The board is involved in business and IT projects to discuss their effect on data quality. The Data Quality Board is usually chaired by the Chief Steward. Dependent on the number of data stewards, they all participate in Data Quality Board meetings. They may also represent the board in business or IT projects touching their area of responsibility. Temporary participants may include the Executive Sponsor or business representatives, such as process owners or business unit managers.

Following the company's structure and objectives, the Data Quality Board has to decide how data stewards are assigned. For example, a business steward may be responsible for a main data type, such as customer or material. Similar, he could be assigned to a process, such as the order or production process. Finally, the assignment to a business unit or geographical region is possible. Answering that question is very complicated and involves many factors. One indicator, however, is the level on which standards are defined and where exceptions are allowed (per data type or per process?). Based on their assignment to areas of responsibility, the number of data stewards is automatically defined.

Chief Steward

The main task of the Chief Steward is to put the board's decisions into practice. He enforces the adoption of standards, helps establishing data quality metrics and targets, and ensures that regulatory, privacy and information sharing policies are followed. In addition, the Chief Steward staffs all data stewards and is their supervisor, but also helps them to enforce their mandates. The Chief Steward is an expert in data quality issues across the enterprise. He needs thorough understanding of business and IT related data quality issues.

Business Data Steward

Business Data Stewards work directly with representatives from business. They document business requirements and assess the impact of new business requirements on data quality and vice versa. Usually, one business data steward is assigned either per business unit, per main business process or per main data type. For their area of responsibility, the business data steward details the corporate-wide data quality standards and policies brought up by the board. His tasks may involve creating business rules for data, developing data models and data vocabularies, implementing data management best practices, and maintaining and publishing data quality metrics. Business Data Stewards know how business terminology is defined in their area and how business processes use data. They communicate their knowledge to the Data Quality Board and recommend standards and policies based on business requirements.

Technical Data Steward

Business Data Stewards counterparts are Technical Data Stewards, who focus on data's representation in IT systems. Similar to their counterparts, one Technical Data Steward can be assigned per business unit or department or per IT system. For their area of responsibility, they provide standardised data element definitions and formats and focus on technical metadata. In addition, technical stewards profile source system details and data flows between systems. They communicate IT-related requirements to the Data Quality Board.

3.3 Decision Areas in Data Quality Management

Data governance refrains from day-to-day decision making, which is part of DQM. Therefore, for the data governance model, only the fundamental decision areas or main activities in improving and maintaining corporate data quality have to be identified. The following decision areas are taken from approaches to DQM (Redman 1996, Wang et al. 1998, English 1999, Nohr 2001, Eppler 2006, Lee & Pipino & Funk & Wang 2006). Engineering approaches dealing with the design of businesses commonly distinguish between different layers regarding strategic, organisational and technical aspects (e.g. Davenport 1993, Hammer & Champy 1993). For the design of DQM, we structure the data quality decision areas according to the layers strategy, organisation and information systems. The following lists main activities at every layer.

Strategy – Design a Data Quality Strategy

A data quality strategy is required to manage and direct all data quality activities in line with the business strategy. The strategy should improve stakeholders' understanding of data quality opportunities and limitations. In addition, data quality should enter the business agenda. Main tasks for setting up a data quality strategy include:

- Analyse and comprehend the role of data within the company.
- Plan concrete data quality initiatives.
- Execute a status-quo assessment of data quality to identify most critical areas for improvement.
- Establish a data quality review process to ensure compliance with laws and regulations.

Organisation – Design the Operational and Organisational Data Quality Structure

Designing the operational and organisational data quality structure includes defining roles and responsibilities, determining information needs, defining metrics and standards, and designing data processes. More particularly, decision areas include:

- Determine information needs of external and internal data consumers.
- Define processes that produce data including adequate controls.
- Define roles and responsibilities for data quality that ensures accountability, authority, and supervision as well as the involvement of senior executives and business management.
- Specify data quality metrics, performance indicators and standards.

- Establish policies and procedures to enforce control, quality assurance, risk management and security.

Information Systems – Design the Data Quality Architecture

The data quality architecture is aligned with and supports the overall enterprise architecture. Designing the data quality architecture encompasses creating a business data repository and defining the information systems in line with data quality requirements. Data quality tools may support the information quality improvement process. The main activities on the information systems layer are:

- Define the data quality architecture design and architecture guidelines.
- Create a business data dictionary to assure consistent understanding of data across the enterprise.
- Define information systems support to increase the accountability for data integrity and security.
- Evaluate and implement tools supporting data quality improvement, such as analysis tools, cleansing and transformation tools or defect prevention tools.

3.4 Assigning Responsibilities

The IT Governance reference framework COBIT defines responsibilities using the RACI chart (IT Governance Institute 2005). RACI is an acronym for the four kinds of responsibilities: who is **R**esponsible, **A**ccountable, **C**onsulted and **I**nformed. Mapped to decision-making processes for data quality they mean:

- Responsible roles actually decide in a data quality decision area.
- Other roles might be accountable, i.e. they provide direction and authorise decisions.
- Consulted roles are asked to provide input and support for decisions.
- The Informed roles are informed about decisions.

COBIT defines one RACI Chart for each IT governance process (cf. Figure 4).

RACI Chart

Activities / Functions	CEO	CFO	Business Executive	CIO	Business Process Owner	Head Operations	Chief Architect	Head Development	Head IT Administration	PMO	Compliance, Audit, Risk and Security
Link business goals to IT goals.	C	I	A/R	R	C						
Identify critical dependencies and current performance.	C	C	R	A/R	C	C	C	C	C		C
Build an IT strategic plan.	A	C	C	R	I	C	C	C	C	I	C
Build IT tactical plans.	C	I		A	C	C	C	C	C	R	I
Analyse programme portfolios and manage project and service portfolios.	C	I	I	A	R	R	C	R	C	C	I

A RACI chart identifies who is Responsible, Accountable, Consulted and/or Informed.

Figure 4. Example: RACI Chart for COBIT Process "Plan and Organise 1 – Define a Strategic IT Plan" (IT Governance Institute 2005, p. 36)

3.5 Contingencies and their Impact

Contingencies impact the distribution of responsibilities (the "Rs", "As", "Cs", and "Is") along the cells in the matrix. The contingencies to IT governance described in Section 2.4 provide indications how data governance's contingencies will impact the data governance model. However, the following is only a first suggestion and needs to be validated and further detailed.

In a strict *centralised data governance approach* all decision-making authority resides in a central DQM role, such as the chief steward or the data quality board (many "A"). The chief steward is employed at the corporate centre. The executive sponsor regularly participates in DQ board meetings and authorises essential decisions, such as the data quality strategy (“A” in some decisions). Decisions made with respect to processes, metrics, standards, architecture, guidelines etc. are valid throughout the whole enterprise. A strict *decentralised data governance approach* places decision-making authority in the hands of business and technical data stewards (many “A”, “R”). A chief data steward might even be obsolete in this design (“C”). Decisions made by the DQ board are recommendations rather than rules or standards (Many “C”, “I”, no “A” alone). Business and technical data stewards decide autonomously for their area of responsibility. The contingencies to the centralised and decentralised model are similar to the ones described in Section 2.4, i.e., performance, corporate governance mode, firm size, diversification mode, diversification breadth, exploitation strategy, and line IT knowledge.

Beside the distinction in centralised and decentralised, data governance models might be cooperative or hierarchical. The *hierarchical data governance model* is characterised by a top-down decision-making approach. Either the chief steward or the data quality board has decision-making authority for a single DQM activity (“A”, separately). The DQ board has few members, usually from first and second level management. Tasks are delegated to business and technical data stewards. However, they will not be directly involved in decision-making (“R”, “I”, few “C”). The *cooperative data governance model* applies formal and informal coordination mechanism to reach decisions. Working groups, task forces, and committees with members from multiple disciplines complement the DQ board (Many “C” and “A”, conjointly). No single role will make a decision on its own. New integrator roles, such as process owners or data architects that report to business units, establish a high-degree of cross-unit collaboration. The hierarchical mode is similar to the centralised mode and similar contingencies apply. Most important is probably low line data quality knowledge and an exploitation strategy using an enterprise-wide consolidation of assets.

4 DISCUSSION

Enterprises need data quality management that combines business-driven and technical perspectives to respond to strategic and operational challenges demanding high-quality corporate data. Data governance specifies the framework for decision rights and accountabilities as part of corporate-wide data quality management. This paper focuses on the accountabilities aspect of data governance and defines a data governance model comprised of data quality roles, decision areas and responsibilities. Instead of following a universal approach, we propose a contingency approach to data governance, which respects that each company requires a specific data governance configuration that fit a set of contingencies. We demonstrate how contingencies form the data governance model.

A data governance model helps companies in structuring their data quality accountabilities. Based on our proposed roles, decision-areas and responsibilities, they can outline their individual data governance configuration. The contingencies and their impact on the model help them to find a configuration that best fit their company. Depending on the level of granularity a company might even define more than one data governance model. For example, they can define one model per decision area or one model for the corporate level and one additional model per business unit.

Finally, a number of limitations need to be considered. This paper describes data governance from an IT governance point of view. Data quality management is not fully comparable to IT management, because of the business perspective involved in DQM; and neither are data governance and IT governance. Still, IT governance research pursues similar objectives; moreover, it has a longer and more profound track record. The research on contingencies influencing IT governance models is used as starting point for our contingency research in data governance. So far, the proposed contingencies and their impact lack validation in the context of data governance. To mitigate the influence of IT governance and for a more elaborate research on the allocation of decision-rights, organisational studies such as corporate governance, organisational theory and organisational psychology need to be considered.

This research has thrown up many questions in need of further investigation. A better understanding of contingencies and their impact needs to be developed. To this end, both organisational literature and empirical studies can be carried out. An analysis of the guidelines and policy aspect of data governance is recommended in order to enforce accountability as defined in the data governance model. For practitioners, the design of a method for defining and implementing the data governance model would help companies to improve and maintain data quality on a sustained basis.

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