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Governing Asset Management Data Infrastructures

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Abstract

Organizations are increasingly looking to trusted data to drive their decision making process. Trusted data has a clear, defined and consistent quality which meets the expectations of the user. Data infrastructures which produce trusted data and provide organizations with the capability to make the right decisions at the right time are socio-technical networks, consisting of technical infrastructures and actor networks, and as such they are often complex and adaptive. Critical issues, challenges, and dilemmas can be identified while looking at data infrastructures as a socio-technical systems. This paper explores conditions and factors for effective and sustainable development of data infrastructures in organizations and suggests that the inherent complexity of data infrastructures requires a multi-faceted way of data governance. Several predefined components of data infrastructures which contain the behavior of agents through various coordination mechanisms have been developed to model the effect of data governance on data infrastructures. These components can be further customized to model an empirical situation more closely. Finally, the paper suggests institutionalization of data governance within an organization as a unifying concept towards the effectiveness and sustainability of data infrastructures, recognizing their inherent complexities. The approach is illustrated with a case study in the asset management domain.

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Keywords: complex adaptive systems; CAS; data infrastructure; asset management; data quality; data governance

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1. Introduction

Asset managers have found it difficult to develop information systems which produce data they can trust, and asset data is regularly observed to be lacking in intrinsic quality, lost within significant amounts of meaningless data, or, conversely, to be missing the required detail[1]. Data governance may support data-driven decision-making by contributing to the improvement of data quality[2]. The objective of this study is to evaluate how data governance supports data-driven decision-making in asset management organizations. This requires looking at the entire data infrastructure and taking an holistic approach to data infrastructures[3] which describes the sociological as well as the technological components. Using a complex adaptive system (CAS) lens can help us to identify and better understand the key elements of data infrastructures and data governance. The organization of data infrastructures occurs through data governance[4]. Data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data[16], ensures that data is aligned to the needs of the organization[11], monitors and enforces compliancy to policy[33], and ensures a common understanding of the data throughout the organization [23]. This research takes place in the asset management (AM) domain of physical infrastructure. We follow Mohseni's [5] (2003) definition of AM as being a discipline for optimizing and applying strategies related to work planning decisions in order to effectively and efficiently meet the desired objective.

AM is often regarded as an essential business process [6]. Quality data is regarded as being essential to driving the decision-making process within AM [7]. In this paper we investigate the impact of data governance on data quality within AM data infrastructures and, as such, the impact of data governance on data-driven decision-making in an AM setting. This study is centered on the AM process of determining current and future asset conditions, critical for assessing the remaining service life of assets and to prevent the risk of failure of assets. In the following section we describe the methods used in this research. In section three, we discuss, on the basis of a review of literature, the factors for effective and sustainable data governance. We describe the results of the case study in section four. In section five we describe a quasi-experiment which quantifies relationships between data governance and improvements in asset management decision-making using an agent-based conceptual model which has been derived from the results of the literature review and the case study. As the experiment is yet to be conducted, discussing the results of the experiment is outside the scope of this article. In section six we discuss the model and the limitations of the quasi-experiment and, finally, we draw conclusions in section seven.

2. Method

The literature review in this research follows the method proposed by Webster & Watson[8] (2002) and Levy & Ellis[9] (2006) and attempts to methodologically analyze and synthesize literature in order to describe key elements of data governance. In November, 2015, the keywords: "data governance", and "principles", returned 17 hits within the databases Scopus, Web of Science, IEEE explore, and JSTOR. 8 hits were journal articles, 6 were conference papers, 2 were books and 1 hit was an article in the press. Of these articles, only 1 article, 10, was directly related to e-governance. We found that most articles covered data governance in general, but few articles included an explicit list of key elements of data governance. We then filtered these results and performed a forward and backward search to select relevant articles based on the criteria that they included a theoretical discussion on what data governance is or does. Based on this forward and backward search, 35 journal articles, conference proceedings and books were selected. Practical sources were only used when the authors provided factual evidence for their assertions.

The case study method used in this research follows the methods proposed by Yin[11] (2009).The case under study was that of asset management within the Directorate General of Public Works and Water Management of the Netherlands. The Directorate General of Public Works and Water Management of the Netherlands is commonly known within The Netherlands as "Rijkswaterstaat", often abbreviated to "RWS", and is referred to as such within this research. The case study was explorative in method and descriptive in nature. Unstructured interviews were held with managers, subject matter experts, and internal consultants. Internal documentation concerned with the description of the data infrastructure of the RWS was studied.

The quasi-experiment described in this paper uses gaming as a tool to simulate data governance in data-driven decision making in an asset management setting. The quasi-experiment follows a pretest-posttest structure. According to Bekebrede [12] (2010), serious gaming can be a useful tool to simulate complex socio-technical infrastructure systems and supports policy makers and designers in understanding the complexity of the planning and design of these systems from the observer perspective [12]. The game is based on an agent based conceptual model of data infrastructures which is used in the quasi-experiment to model real-world situations.

3. Literature Review

In this research elements of data infrastructures are modeled from a CAS perspective[3, 14]. Data infrastructures consist of *components*[15], which are embodied by data and technology. A*gents* [16] interact with one another within a certain *schema*[17]. Schema refers to shared rules which are embodied by norms, values, beliefs, and assumptions.

Many scientific sources follow the information governance definition of Weill and Ross[18] (2004) and define data governance as specifying the framework for decision rights and accountabilities to encourage desirable behavior in the use of data[4]. Practitioners tend to disagree with this generalization and DMBOK defines data governance as, "the exercise of authority, control, and shared decision making (planning, monitoring and enforcement) over the management of data assets"[19] pp. 37. Theoretically, data governance describes the processes, and defines responsibilities. Data managers then work within this framework. Four key elements of data governance were identified during the literature review: 1. Organization; 2. Alignment; 3. Compliancy; 4. Common Understanding. These key elements are presented individually in detail in the following paragraphs.

Most researchers agree that data governance has an *organizational* dimension 4. For example, Wende & Otto[20] (2007) believe that data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data. Also, Thompson et al.[10] (2015) show that coordination of decision making in data governance structures may be seen as a hierarchical arrangement in which superiors delegate and communicate their wishes to their subordinates, who in turn delegate their control.

Data governance should ensure that data is *aligned* with the needs of the business[21]. A data governance program should demonstrate business value[22]. Describing the business uses of data establishes the extent to which specific policies are appropriate for data management. Data could be a reusable asset if used correctly[21], as data is a virtual representation of an organization's activities and transactions and its outcomes and results. Data governance should ensure that data is "useful"[23]. This line of thinking is also in line with a common definition of data quality as being "fit for use" [24]. A data quality strategy is required to ensure that data management activities are in line with the overall business strategy[20].

Data governance includes a clearly defined authority to enforce *compliancy* to data policies and procedures[25]. Panian[21] (2010) states that establishing and enforcing policies and processes around the management data is the foundation of an effective data governance practice. Mechanisms need to be established to ensure organizations are held accountable for these obligations through a combination of incentives and penalties[26] as governance is the process by which accountability is implemented[27]. In such a manner, accountability can unlock further potential by addressing relevant problems of data stewardship and data protection in emerging data ecosystems.

Governing data appropriately is only possible if there is a *common understanding* of data and it is properly understood what the data to be managed means, and why it is important to the organization[28]. Attention to business areas and enterprise entities should be the responsibility of the appropriate data stewards who will have the entity-level knowledge necessary for development of the entities under their stewardship[28]. Khatri & Brown[4] (2010) believe that there is a need to manage changes in metadata as well.

A common metric used to measure the effectiveness of data governance is data quality[29]. Data governance, data quality and data (quality) management are closely linked and are often handled by the same individuals in organizations[30]. In this regards, data governance is important for decision making with regard to data quality management[31]. According to Strong et al.[24] (1997), data quality is typically determined by the data's fitness for use, which is the capability of data to meet the requirements of the user in order to accomplish a certain goal in a given context. A user can only decide whether or not data is fit for use if the quality of the data is known and reported. This makes it important for organizations to define data quality metrics, which can be used to measure and report the quality of data based on well-defined data quality dimensions. Wang and Strong[32] (1996) identify four *dimensions* of data quality and one hundred and eighteen *aspects* of data quality. This research follows Otto[29] (2011) and Wang & Strong[32] (1996) and addresses only the commonly used quality aspects of completeness, consistency, accuracy, relevancy, and timeliness[29, 32]. We follow the definitions of these terms as proposed by Pipino et al.[33] (2002).

4. Case Study: Data Governance at RWS

The core function of AM at RWS is that objects such as roads, viaducts, or bridges are managed so that they fulfill the function they have in the network. To operate effectively, RWS focusses on being able to make the right choices with regards to management and maintenance[34]. Choices must be made in the way the bridge or viaduct is maintained, but these choices are not always straightforward, as, for example, during maintenance procedures of bridges or viaducts, roads still need to be accessible. In order to make these choices, RWS requires data that can be trusted to conform to the quality that is required. RWS bases its asset management processes on data-driven decision-making.

In order to maintain their asset management data system, RWS has developed a data management organization which implements and enforces uniform data entry and data management protocols and processes. This data management organisation encompasses a wide variety of agents. Within the data management process, there are many different organisational levels, each level and each link in the information chain acing as an agent in the process. For example, divisions of RWS are organised according to geographic location, and each division is an independent agent. Each independent division implements standardised processes in their own way, and each individual advisor, in his turn, is capable of acting independently. RWS is structured hierarchically in divisions and functionally in processes. The AM process owner is a member of the Executive Board as is the Information process owner, the Chief Information Officer (CIO). In principle, ownership of the data is given to the AM process owner. The CIO is responsible for ensuring the availability of functionality required to manage and use the data, but the responsibility for the quality of the data lies with the AM process owner. In general, the process owners operate at a strategic level. The process owners normally delegate tactical decisions to divisional or department heads whose work area is closest related to the data set. Operational decisions are normally delegated to domain teams which include domain architects, functional managers, information managers and data managers. The domain teams usually have a mix of both business related functions as IT related functions. The CIO is aided in his/her decision-making by a Chief Data Officer (CDO). The main role of the CDO is to bridge the management gap between the executive (strategic) level and the operating (tactical) management processes with regards to data (quality) management. Notably, the CDO does not have a data ownership role. For example, RWS has decided to introduce a number of “base” registrations in an effort to consolidate the data portfolio of RWS. Each registration, such as the area information registration (AIR) which includes data regarding the status of the physical infrastructure under RWS’s management, is owned by the relevant process owner. In the case of AIR, the data owner is the AM process owner. The delegated owner, or “steward” is the chairman of the regional divisions whose responsibility is the maintenance of physical infrastructure within their geographical area. The steward works with the CDO and the Lead Data Architect to coordinate the domain teams which are responsible for the development of these data sets.

5. A Quasi-Experiment To Quantify The Relationship Between Data Governance And Improvements In Asset Management Decision-Making Using An Agent-Based Conceptual Model

An experiment is a study in which an intervention is deliberately introduced to observe its effects[35]. A quasi-experiment[36] is an empirical study used to *estimate* the causal impact of an intervention on its target population[37]. Quasi-experiments share similarities with experimental design, but they lack the element of random assignment to treatment or control[37]. In this study the choice was made for a quasi-experiment as opposed to a true experiment as full control over the scheduling of experimental stimuli that make a true experiment possible is lacking [36] and because we wish to retain control over selecting and scheduling measures and how the treatment will be organized[35]. The quasi-experiment follows a pre-test/post-test structure and will be conducted as follows. Firstly, the quasi-experiment will be introduced to the participants and instructions will be given. Secondly, the pre-test, a participant survey, will be conducted to measure various background characteristics of the participants, as well as their experience with asset management, data governance, and with serious gaming. Thirdly, participants will be asked to complete scenario tasks within the game environment. Fourthly, a post-test in the form of a second participant survey will be used to measure the extent to which data governance influences the completion of the scenario tasks within the game. Finally, in a plenary discussion the participants will be questioned as to the levels of difficulty of the tasks and if they have any suggestions to improve the game or the application used for data governance.

Derived from the elements of data governance outlined in the literature review and the case study, we propose four key elements to improve data governance: 1. Coordination mechanisms; 2. Definition of data quality requirements; 3. Monitoring of data quality; 4. Shared data commons. Although there may be other ways to improve data governance, these infrastructure elements were found to be critical. Based on these key elements, the following design propositions were generated:

1. Coordination mechanisms positively influence data quality in asset management organizations
2. Making data quality requirements explicit positively influences data quality in asset management organizations
3. Monitoring data quality positively influences data quality in asset management organizations
4. Creating a shared data commons positively influences data quality in asset management organizations.

Within experiments, independent variables are systematically varied, and dependent variable(s) are quantitative, objective measures of system performance[37]. We aim to evaluate data governance in a game setting in which participants use a prototype application to specify the coordination mechanisms for decision rights and accountabilities, to ensure that data is aligned to the needs of the organization, to monitor and enforce compliancy, and to ensure a common understanding of the data. At the same time we aim to control the variables to test our propositions and to ensure that the effects can be contributed to data governance. Figure 1 shows the variables involved in the quasi-experiments.

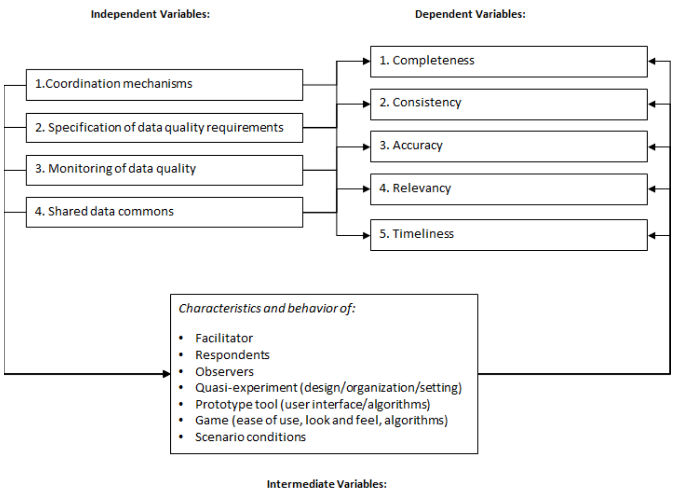

Figure 1: Variables involved in the quasi-experiments

We use gaming as an instrument to simulate data governance in data-driven decision-making in an asset management setting. Serious gaming can be a useful instrument to simulate complex socio-technical infrastructure systems and supports policy makers and designers in understanding the complexity of the planning and design of these systems from the observer perspective[12]. At the same time, gaming is an experience space in which participants can experience the complexity themselves and increase their understanding of the system, from the player perspective.

The game setting is a model of the asset management data infrastructure. Our model breaks up the data infrastructure into reusable, logical parts. Within the model, all independent actors are viewed as agents - autonomous, goal driven entities that are able to communicate with other agents and whose behavior is affected by their observations, knowledge and interactions with other agents[16]. Within the game setting, each agent has a particular role to play, based on their position within the organization and the underlying processes. In agent-based simulations, the agents interact in a simulated environment, where modelling reductions have been applied[16]. By placing the agents in an agent-based simulation, it should be possible to study the impact of data governance on data quality, both in detail and over a prolonged period of time, where the experimental conditions can be manipulated[16].

Simulation strives to develop a dynamic model of the system and experiment with this model as well as with possible alternative models in order to attempt to understand a known problem[40]. In this quasi-experiment, participants will be required to maintain assets in a virtual world, using data provided to them by the “game-master”. Virtual worlds allow researchers to explore existing theory and develop new theory in a variety of fields, including information and social sciences[41]. Within their virtual world, each player will be allocated “assets” which they will be required to manage and maintain based on the data provided to them. The state of the assets will degrade during the course of the game, and will need to be maintained. In a second application, players will be able to govern their data using the functional elements described in the design propositions. Depending on their allocated group, players will have access to varying degrees of functionality. This allows the researcher to manipulate the variables within the game setting in order to test the four design propositions. For example, at the start of the game, players may be given the opportunity to define the required quality of the data provided to them, and, depending on the game settings, define who is responsible for maintaining the quality of each dataset. The control group will not have any access to the second application, but will be granted access to the same data.

6. Discussion

The objective of the research is to identify and model key elements of data governance in data infrastructures. We view data infrastructures through a CAS lens. In CAS the system is composed of agents that interact with each other and affect the system. Using a CAS lens can help us to identify and better understand the key elements of data infrastructures and data governance. The research methods used are a literature review, and an analysis of a data infrastructure case study. We also describe a quasi-experiment to quantifiably investigate the relationships between data governance and data quality. The literature review provided us with an overview of the existing body of knowledge and gave us a theoretical foundation for the research topic whilst also providing definitions for the key concepts. Case study research is a widely used qualitative research method in information systems research, and is well suited to understanding the interactions between information technology-related innovations and organizational contexts[42]. Data governance is a complex undertaking, and data governance projects in government organizations have often failed in the past. There is not one, single, “one size fits all” approach to the organization of data governance[20]. Decision-making bodies need to be identified for each individual organization, and data governance should have a formal organizational structure that fits with a specific organization. Researchers have proposed initial frameworks for data governance[4] and have analysed influencing factors [44] as well as the morphology of data governance[45]. A number of data governance elements have emerged out of this research - organization, alignment, monitoring and enforcement of compliance, and common understanding. A common metric used to measure the effectiveness of data governance is data quality[2]. Data quality is often determined by the data’s fitness for use, which is the capability of data to meet the requirements of the user in order to accomplish a certain goal in a given context. A user makes decisions on the usability of the data based on the known quality of the data. This makes it important for organizations to define data quality metrics based on well-defined data quality dimensions.

Quasi-experiments are subject to concerns regarding internal validity, because the treatment and control groups may not be comparable at baseline[46]. With quasi-experimental studies, it may not be possible to convincingly demonstrate a causal link between the treatment condition and observed outcomes. This is particularly true if there are confounding variables that cannot be controlled or accounted for, such as if the design of the experiment does not control for the effect of other plausible hypotheses that could have improved performance between the pretest and the posttest [37]. For example, external influences may occur between the pretest and posttest that could explain the results. If the selected group represent either the very best or very worst performers, then it is possible that pretest-posttest differences could be affected by statistical regression to the mean. In this experiment, the evaluations focus on a limited number of specific tasks related to the coordination framework, data quality definitions, data quality monitoring and the shared data commons which need to be conducted within a limited time frame. Participants may not be able to complete the scenarios within this time frame. Also, three types of measures are used in the evaluations, namely time measures, observations and questionnaires. In addition to these three measures, other measures, such as other data quality aspects, of the performance of the participants may be used. By using additional measures, more information may be obtained regarding the contribution of data governance to decision-making in asset management organizations. Moreover, other factors may influence the outcomes, such as the user interface, quality of the game or data governance application, experience with gaming, and experience with information management in general. The final results may therefore not only be attributed to the coordination framework, the definition of quality requirement, the monitoring of data quality or the shared data commons.

7. Conclusions

Public organizations are facing increasing challenges to the management of their infrastructure assets and many AM organizations are looking for ways to improve the efficiency and effectiveness of their AM processes through data-driven decision-making. Data governance specifies the framework for decision rights and accountabilities to encourage desirable behavior in the use of data[16], ensures that data is aligned to the needs of the organization [11], monitors and enforces compliancy to policy[33], and ensures a common understanding of the data throughout the organization [23.] In this paper we describe a quasi-experiment to assess how aspects of data governance - a coordination framework, data quality definitions, data quality monitoring and a shared data commons - affect the commonly used quality aspects of completeness, consistency, accuracy, relevancy, and timeliness. The assumption is made that asset management decision-making is data-driven and that better quality data results in better decision-making. The quasi-experiment detailed in this paper uses gaming as an instrument to simulate the implementation of data governance in data-driven decision making in an asset management setting. This experiment does have limitations as quasi-experiments are subject to concerns regarding internal validity, because the treatment and control groups may not be comparable at baseline and it may not be possible to convincingly demonstrate a causal link between the treatment condition and observed outcomes.

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