A Leadership and Governance Stage Model (LGSM) in Digital Transformation in Data Management

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Abstract: In this era of digital transformation, organisations and individuals have the ability to generate, collect, process, and analyse a vast volume of data to gain benefits and valuable insights. However, despite recognising the competitive advantage of digital transformation in data management, they often face challenges in navigating the transformation process and aligning their existing practices with on-premise technologies. Leadership and governance play a very significant role in digital transformation procedures. The main objectives of this research are 1) to establish a Leadership and Governance Stage Model (LGSM), which provides a standardised, structured, and objective roadmap for organisations to determine their current leadership and data governance maturity stage in digital transformation in data management and 2) to guide organisations in progressing to the next maturity stage by using LGSM as a framework. This research adopts a qualitative approach, utilising a Systematic Literature Review (SLR) conducted over the past ten years, applying Grounded Theory. A total of 14 well-defined Capability Maturity Models (CMMs) of data management were reviewed, summarised, and consolidated. In this way, LGSM is established, comprising six stages: Stages 0, 1, 2, 3, and 4, with Stage 5 representing the most developed and mature stage. The holistic view of this stage model has been summarised at the end of this research, which demonstrates the significance of leadership and governance in digital transformation.

Keywords: Data management, Capability maturity model, Stage model, Digital transformation, Data governance, Leadership

1. Introduction

This paper underscores the importance and maturity stages of digital transformation in data management. In today's data-driven landscape, data management is pivotal (Meng, 2019; Ahsan *et al.*, 2022). With organisations and individuals producing vast amounts of data daily, effective management and utilisation of this data have become paramount for success (Adrian *et al.*, 2016). Data management's significance permeates various dimensions, influencing numerous facets of business operations, decision-making, innovation, and regulatory compliance (Hribar Rajterič, 2010; Barua, Mani and Mukherjee, 2012; Cai and Zhu, 2015; Ahmed Zainul Abideen *et al.*, 2021). By leveraging data effectively, organisations can unearth invaluable insights, attain a competitive edge, and effect significant change in their industries (Ahsan *et al.*, 2022; Alsayed and Aqel, 2022). Thus, proficient data management is essential for organisations aiming to expedite and enhance their decision-making processes.

For more sophisticated data analysis, organisations must gather vast amounts of data (Forum, 2018; Abraham, Schneider and vom Brocke, 2019). This encompasses structured data from within the organisation, such as financial reports, inventory data, and customer transactions, as well as unstructured data from external sources like clickstreams, text documents, emails, and sensor data (Abraham, Schneider and vom Brocke, 2019). Digital transformation becomes vitally important when aiming to effectively manage and leverage these data (Baranauskas and Raišienė, 2022). Data from the World Economic Forum in 2018 suggests that by 2030, 70% of organisations will reap the benefits of digital transformation, leading to enhanced value (Forum, 2018). The significance of digital transformation became especially evident post-COVID-19, and people recognised its importance across several domains, including remote work and collaboration, business continuity, digital customer engagement, data-driven decisions, scalability, flexibility, and cost efficiency (Hai, Van and Thi Tuyet, 2021). For a comprehensive digital transformation anchored in data lifecycle management—which encompasses steps such as data acquisition, data documentation, data quality control, data analytics, data preservation, and data visualisation—organisations must contemplate the distinct requisites of each phase (Halper and Stodder, 2014; Qin, Crowston and Kirkland, 2014; Hernandez-Hall, 2021). At the same time, every step in the data lifecycle management process demands consideration of multiple facets including strategic planning, strong leadership and governance, capability evaluation, methodical resource allocation, targeted training and development, and consistent process assessments related to it (Halper and Stodder, 2014; Qin, Crowston and Kirkland, 2014; Hernandez-Hall, 2021). These must be meticulously considered and outlined to facilitate a triumphant digital transformation in data management.

This research mainly focuses on improving the leadership and governance in digital transformation from the perspective of data lifecycle management. In the progress of realising digital transformation, leadership and

governance play a significant role (Cai and Zhu, 2015; Hernandez-Hall, 2021). Effective leadership provides a clear vision and strategy for digital transformation, facilitating that all efforts are aligned toward a common purpose (Cai and Zhu, 2015; Hernandez-Hall, 2021). Additionally, leadership plays a critical role in driving change, fostering a digital-first mindset, and encouraging the adoption of new technologies and practices (Hernandez-Hall, 2021). Robust governance facilitates that decisions are based on data, well-considered, and consistent with the organisation's overarching goals (Halper and Stodder, 2014; Qin, Crowston and Kirkland, 2014; Hernandez-Hall, 2021). Also, governance helps in allocating resources effectively, prioritising initiatives, and monitoring that resources are used efficiently (Qin, Crowston and Kirkland, 2014). Therefore, this research aims to explore the current maturity and performance of an organisation's leadership and data governance in the progression of digital transformation in data management. It assesses where organisations currently stand and the potential paths they can take in the future to expedite the realisation of benefits from digital transformation in data management. To precisely determine an organisation's current position in this journey, this paper introduces the Leadership and Governance Stage Model (LGSM).

Stage Model also called the Capability Maturity Model (CMM), was initially published in the book "Managing the Software Process" by Watts Humphrey in 1989 (Humphrey, 1989). The concept of maturity plays a significant role in assessing the progress and readiness of organisations, and it encompasses a continuum that ranges from extreme immaturity to extreme maturity (Humphrey, 1989). Maturity models provide a framework for identifying the strengths and weaknesses of a particular domain or organisation (Humphrey, 1989). By utilising maturity models, organisations can gain valuable insights into their current capabilities and identify areas for improvement (Hernandez-Hall, 2021). These models codify best practices, allowing organisations to benchmark their performance against established standards (Vesset *et al.*, 2015; Klievink *et al.*, 2017). Therefore, the main objectives of this paper are: *1) to establish LGSM, which provides a standardised, structured, and objective roadmap for organisations to determine their current leadership and data governance maturity stage in digital transformation and 2) to guide organisations in progressing to the next maturity stage by using the this stage model as a framework.* This research is qualitative in nature, employing Grounded Theory as its methodology. The authors have reviewed papers pertaining to leadership and governance in digital transformation for data management over the past ten years, with 14 papers scrutinized in depth. By amalgamating insights from these 14 papers, a comprehensive and precise LGSM has been developed.

2. Systematic Literature Review for the Last ten Years

2.1 The Research Scope for LGSM in Data Management

After conducting a comprehensive literature review, it was discovered that only a few specific CMMs related to data management have been documented. Most maturity models are about Business Intelligence (BI) (Hribar Rajterič, 2010; Chuah and Wong, 2013; Fedouaki, Okar and Alami, 2013; Treviño and Gamboa, 2014), Artificial Intelligence (AI) (Raghad Baker Sadiq *et al.*, 2021a, 2021b), IoT applications (Asdecker and Felch, 2018; Klisenko and Asensio, 2022), Project Management ('Using the project management maturity model; strategic planning for project management, 2d ed.', 2005; Chang and Wei, 2013; Farrokh and Mansur, 2013; Meng, 2019; Araújo, 2020) and data warehouse (Hidayanto *et al.*, 2022). However, data management is the foundational process of creating, obtaining, storing, protecting, and processing data to ensure its accessibility, reliability, and timeliness. Everything else – BI, AI, IoT, data warehouses – relies on proper data management (Comuzzi and Patel, 2016). In the past decade, there has been a paucity of research regarding CMMs of leadership and governance in the realm of data management. This research therefore concentrates on digital transformation within this area. To develop the LGSM, the authors exclusively consolidate and delineate the domains of leadership and data governance as they relate to data management CMMs.

2.2 Databases and Search Strings for LGSM

To establish a more comprehensive and precise LGSM, a ten-year Systematic Literature Review was conducted in this research. Based on the results generated by the search strings shown in **Table 1** that were created by the author, there are several databases were used in this research:

- ProQuest ABI/INFORM Global,
- ProQuest ABI/INFORM Trade & Industry,
- ProQuest Dissertations & Theses Global, and
- ProQuest SciTech Premium Collection,
- Web of Science,
- Engineering Village.

At the end of the third round of SLR, there are 14 papers in total associated with CMMs for data management.

Table 1: Databases and Search Strings for LGSM

Database	Search String(s)
ProQuest ABI/INFORM Global ProQuest ABI/INFORM Trade & Industry ProQuest Dissertations & Theses Global ProQuest SciTech Premium Collection	((ti(capability maturity model) OR ti(maturity model) OR ti(capability model) OR ti(stage model) OR ti(conceptual framework)) AND (ti(data management) OR ti(leadership) OR ti(governing big data) OR ti(big data application) OR ti(data governance) OR ti(big data))) AND pd(20120426-20220426) .
Web of Science	data management (Title) or leadership (Title) or governing big data (Title) or big data application(Title) or data governance (Title) or big data (Title) 2012-04-26 to 2022-04-26 capability maturity model (Title) or maturity model (Title) or capability model(Title) or stage model (Title). 2012-04-26 to 2022-04-26
Engineering Village	(((((capability maturity model OR maturity model OR stage model) WN TI) AND ((data management OR leadership OR governing big data OR big data application OR data governance OR big data) WN TI))) AND ((2022 OR 2021 OR 2020 OR 2019 OR 2018 OR 2017 OR 2016 OR 2015 OR 2014 OR 2013) WN YR))

3. Research Method

3.1 Grounded Theory with Nvivo

In this research, Grounded Theory, a qualitative analysis method, serves as the main analytical tool for the systematic literature review (SLR), which was introduced by Glaser and Strauss in their 1965 book "Awareness of Dying" (Barney and Anselm, 2017). This research utilised Nvivo to employ Grounded Theory in a systematic literature review, aiming to craft a more encompassing data management capability maturity model. The 14 papers linked to data management maturity models were integrated into Nvivo. The research process commenced with line-by-line coding or “open coding” using Nvivo, spotlighting and categorising salient concepts from the papers into subcategories, and subsequently, main categories. Essentially, the material was dissected into conceptual chunks, termed as different “codes” (Bringer, Johnston and Brackenridge, 2006). The SLR's final phase saw the researcher compare and summarise these codes to grasp their inherent meaning. This led to the extraction of each paper's core elements, which were then amalgamated across different stages and dimensions to formulate the Leadership and Governance Stage Model (LGSM) presented in this research.

4. The Description of Each Stage in LGSM

This research examines leadership and governance in digital transformation for data management. Leadership involves top managers guiding the organisation to realise its significance and take action for digital transformation. Data governance means setting policies and monitoring the processes of digital transformation in data management. It defines roles, ensures clear communication, and uses metrics to measure and improve effectiveness. As **Figure 1** shows below, to precisely illustrate the evolution of leadership and governance in digital transformation pertaining to data management, the LGSM has been introduced, and anchored in seven dimensions: ***Data Acquisition, Documentation and Quality, Data Description and Representation, Data Dissemination and Sharing, Data Repository Services and Preservation, Data Analysis, Budget, and Operational Infrastructure***. By consolidating and summarising the domain of leadership and data governance from the previous 14 CMMs, six stages, ranging from Stage 0 to Stage 5, have been delineated below to characterise the maturity levels of leadership and governance in digital transformation.

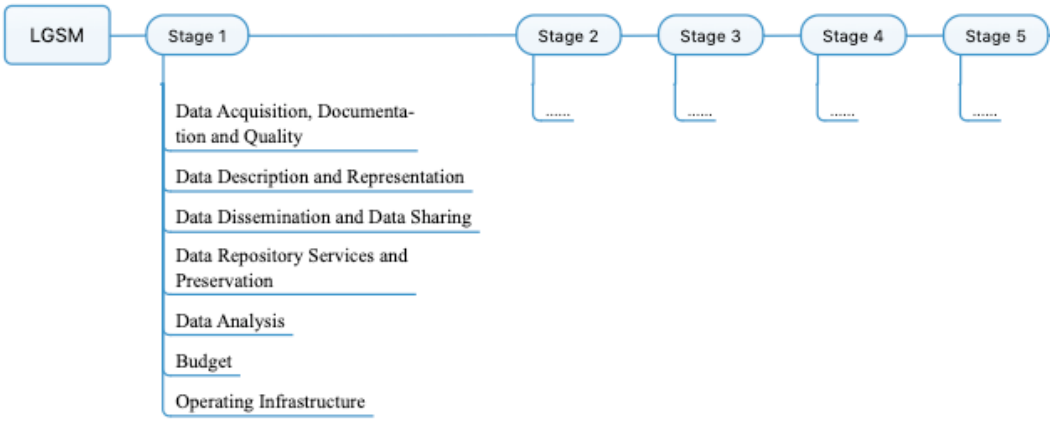

Figure 1: Structure of LGSM

4.1 Stage 0 – Ignorance

In stage 0, "Ignorance", is where the organisation has no capabilities or any knowledge of data management. The importance of data management does not appear to be a component of the organisation's core beliefs, so there is a lack of knowledge about how to store and use data by staff and top managers (Qin, Crowston and Kirkland, 2014; Farah, 2017). In addition, there is a lack of leadership in policy establishment in data collection, documentation, quality control, data visualisation, data sharing, data analytics, budget allocation and operating infrastructure (Halper and Stodder, 2014; Sulaiman, Cob and Ali, 2015; Comuzzi and Patel, 2016). There are no data structures and no data management strategy at this stage, and data is created by manual observation and recorded in notes individually or by small groups of people (Halper and Stodder, 2014; Sulaiman, Cob and Ali, 2015; Comuzzi and Patel, 2016). Therefore, there are no typical data management procedures and processes, data analytics, data visualisation tools, or any infrastructure or IT solutions at this stage. Senior managers and staff are not aware that money should be spent on data management (Qin, Crowston and Kirkland, 2014).

4.2 Stage 1 – Considering and Exploring

Stage 1, "Considering and Exploring", is where some individuals and top managers are considering minimally about data management, but still, most of the employees are unsure of how data management links to the enterprise's objectives. The culture of technical data management has been entrenched in a negative way towards IT-driven innovation (Zitoun *et al.*, 2021). Some staff say that data management is very important for the company, but most say that it is not very important at all (El-Darwiche *et al.*, 2014). Still, there is a lack of leadership in policy establishment in data collection, documentation, quality control, data visualisation, data sharing, data analytics, budget allocation and operating infrastructure (Qin, Crowston and Kirkland, 2014; Vesset *et al.*, 2015; Olszak and Mach-Król, 2018a). Investment justification is not required as the budget is solely focused on basic business operations and does not include data quality audits (Vesset *et al.*, 2015; Hernandez-Hall, 2021). The operational decision is made solely based on senior managers' experience and beliefs (Qin, Crowston and Kirkland, 2014; Vesset *et al.*, 2015; Olszak and Mach-Król, 2018a). A data management strategy cannot be created because there aren't any dedicated resources and no staff have data skills (Comuzzi and Patel, 2016; Olszak and Mach-Król, 2018a; Herselman, Wayi and Olaitan, 2019; Hernandez-Hall, 2021; Zitoun *et al.*, 2021). Some staff members are primarily motivated by a personal interest in data management, but lack the necessary skills to keep up with the rapid rate of technological change (Comuzzi and Patel, 2016; Olszak and Mach-Król, 2018a; Herselman, Wayi and Olaitan, 2019; Hernandez-Hall, 2021; Zitoun *et al.*, 2021).

4.3 Stage 2 – Understanding and Practising

In stage 2, "understanding and practising", where data needs and benefits of data management have been noticed initially, and the organisation has started formal data analytics, descriptive analytics is used in this stage, which aims to evaluate the previous performance of the firm. Staff members sometimes talk about the idea or technology behind the data management (El-Darwiche *et al.*, 2014; Sulaiman, Cob and Ali, 2015; Hernandez-Hall, 2021). When employees see that data management technology can help their company meet its goals, they try it out (Vesset *et al.*, 2015; Comuzzi and Patel, 2016). Staff from the IT department have looked into and worked on their data management knowledge and skills (Vesset *et al.*, 2015; Comuzzi and Patel, 2016). For leadership and data governance, the data management policies have been codified for ad-hoc projects rather than the entire organisation, for instance, policies related to data collection, data documentation and data

quality checks have been established at the department level or business units such as the policies of data naming standards (Halper and Stodder, 2014; Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016) . The organisation has a strategic mission and goals for initiating data collection and/or utilisation (Hernandez-Hall, 2021). The policies related to data description and representation have been codified for ad-hoc projects, such as policies related to the metadata establishment (Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016). Also, the policies related to data sharing and data confidentiality have been codified for ad-hoc projects (Halper and Stodder, 2014; Qin, Crowston and Kirkland, 2014). However, the policies related to data analytics, budget allocations, and operating infrastructures have not been codified in the organisation. For budget allocation, the budget is decentralised and based on individual department plans the budget is decentralised and based on individual department plans or ad-hoc projects (Vesset *et al.*, 2015; Hernandez-Hall, 2021). Investment justification is required for a clearly defined operational problem or needs (Vesset *et al.*, 2015). For operating infrastructure, the organisation installs and deploys infrastructures on an ad-hoc basis (Vesset *et al.*, 2015; Comuzzi and Patel, 2016). There is no defined architecture for operating infrastructure (Vesset *et al.*, 2015; Comuzzi and Patel, 2016). Data management tools are mostly used by people who have a lot of experience with technology (Hernandez-Hall, 2021; 'Hortonworks-Big-Data-Maturity-Assessment.pdf', no date).

4.4 Stage 3 – Defined and Managed

In stage 3, "Defined and managed", where data needs and benefits have been addressed at the department level, to find out the problems that exist in daily operations, the organisation starts doing diagnostic analytics at this stage. The company has a positive and proactive attitude about how to manage its data (El-Darwiche *et al.*, 2014; Qin, Crowston and Kirkland, 2014; Herselman, Wayi and Olaitan, 2019; Zitoun *et al.*, 2021). For leadership and governance, there is at least one executive sponsor of data management, and the organisation places a high value on evidence-based operations and decisions at all levels of the organisation. Staff members understand how data management can impact operations and decision-making processes and are all actively involved in the data management tool's use (Botcheva, White and Huffman, 2002; Qin, Crowston and Kirkland, 2014; Farkas, Hinchliffe and Houk, 2015; Farah, 2017). Different departments' staffs have accessed, addressed, and defined data management knowledge and abilities (Qin, Crowston and Kirkland, 2014). Each department has an obligation to provide input on data management technologies and tools (Zitoun *et al.*, 2021). The policies related to data collection, data documentation and data quality checks, data description and representation, data sharing and data confidentiality, data preservation, data curation, and data backup have been established at least at the department level, and most of them have been defined throughout the entire organisation (Halper and Stodder, 2014; Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016). Besides, the organisation is considering establishing some policies related to data analytics aligning with its business objectives (Sulaiman, Cob and Ali, 2015). For budget allocation, there is a mixed budget structure utilised in the entire organisation, including centralised and decentralised budgeting (Vesset *et al.*, 2015). Except for the normal procedures and processes, before the investment in data management, the organisation decides to utilise Proof of Concepts (POCs) to evaluate new data, tools, technologies and equipment (Farah, 2017). For operating infrastructure, Key Performance Indicators (KPIs) are solely applied to measure the technology initiatives (Vesset *et al.*, 2015). People at the organisation have a defined plan that includes goals to improve how they collect and use data, and there is a roadmap is being drawn up for all data management projects to follow (Clarke, 2012; Halper and Stodder, 2014; Farkas, Hinchliffe and Houk, 2015). Business leaders say they will spend more money to improve and keep an eye on their data management strategy (Gantz and Reinsel, 2011; Qin, Crowston and Kirkland, 2014; Hernandez-Hall, 2021). Job descriptions for IT departments include data management duties (Halper and Stodder, 2014; Qin, Crowston and Kirkland, 2014; Hernandez-Hall, 2021)When necessary, free on-the-job training, including data training, is offered for specific project requirements (Halper and Stodder, 2014; Hernandez-Hall, 2021).

4.5 Stage 4 – Standardised and Intelligent

Stage 4, "Standardised and intelligent", is where the majority of employees in the organisation have faith in the advantages of data management, and data needs, data management policies, and quantitative quality goals have all been set throughout the entire company (Qin, Crowston and Kirkland, 2014). Besides the descriptive and diagnostic analytics, the organisation has started doing predictive analytics for the decision-making process (Halper and Stodder, 2014; Zitoun *et al.*, 2021). For leadership and data governance, data management is fully supported by the top management (Olszak and Mach-Król, 2018a). It is important for everyone in an organisation to know and accept the value of good data management (Halper and Stodder, 2014; Comuzzi and Patel, 2016). All employees, including those in the information technology and business departments, are fully knowledgeable about data management technology and tools (Halper and Stodder, 2014; Comuzzi and Patel,

2016). All the policies, procedures and processes related to data collection, data preservation, data visualisation, data sharing, and data analytics have been defined throughout the entire organisation (Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016; Hernandez-Hall, 2021). In addition, policies related to data definition, data lineage and data usage have been defined throughout the organisation (Vesset *et al.*, 2015; Comuzzi and Patel, 2016). There is a governance committee to oversee data quality management (Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016; Hernandez-Hall, 2021). To assess the effectiveness of data usage, the quantitative matrix for data governance has been defined such as KPI and Service Level Agreements (SLAs) (El-Darwiche *et al.*, 2014; Qin, Crowston and Kirkland, 2014). There is a central architecture board composed of experts and stakeholders who have defined the guidelines and standards in order to govern the deployment of technologies, tools, and equipment (Vesset *et al.*, 2015). For budget allocations, a permanent budget line associated with data management has been carried out throughout the entire organisation, and there is a mixed strategy of utilising centralised, decentralised, and ad-hoc budget allocation in the organisation (Vesset *et al.*, 2015; Comuzzi and Patel, 2016; Hernandez-Hall, 2021). Ownership of the improvement of data management is defined, as gaining ownership of high KPIs and improving data management, staff are becoming more proactive in defining process/data ownership (King and Kraemer, 1984; Olszak and Mach-Król, 2018a; Hernandez-Hall, 2021). At this stage, the main goal of governance is the balance between data needs including relevant, timely and consistent data for analytics and data confidentiality issues (Halper and Stodder, 2014). Data management responsibilities are included in the job descriptions of the majority of employees who handle data, and training is given for all the tasks in the organisation at a charge (Halper and Stodder, 2014; Vesset *et al.*, 2015). The organisation has a business plan in place that includes objectives for expanding data use beyond present practices, and quantitative quality goals have been set up for monitoring the effectiveness of data and operation management (Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016).

4.6 Stage 5 – Optimised and Innovating

In stage 5, "Optimised and innovating", data management facilitates operations, and evidence-based decision-making is fundamental to the organisation's culture and leadership style (Olszak and Mach-Król, 2018b). The company uses prescriptive analytics, which has enabled both internal and external use of structured and unstructured data analytics for the innovation (Halper and Stodder, 2014; Klievink *et al.*, 2017). For leadership and data governance, all policies, procedures and processes related to data acquisition, documentation and data quality control, data sharing, data preservation, data visualisation, data analytics, and operating infrastructures have been evaluated on a regular basis based on the quantitative quality feedback from the entire organisation (Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016). Specifically, there are formalised quantitative approaches, procedures, and processes that have been established to evaluate the performance, strategies and initiatives of these data management activities (Qin, Crowston and Kirkland, 2014; Comuzzi and Patel, 2016). In order to learn from other businesses and find more cutting-edge technologies and solutions, information and data management skills have been shared internally and outside from the standpoint of the organisation (Qin, Crowston and Kirkland, 2014; Carvalho *et al.*, 2019). The long-term data management plan has been established and is being regularly reviewed and monitored. All employees of this organisation have job descriptions that include information on data management duties (Herselman, Wayi and Olaitan, 2019). The organisation offers free data training to all of its employees (Hernandez-Hall, 2021).

5. Discussion and Conclusion

After reviewing a decade's worth of Capability Maturity Models (CMMs) related to data management, this paper presents a refined Leadership and Governance Stage Model (LGSM). Using Grounded Theory, the authors amalgamated leadership and data governance domains from 14 CMMs. The model begins with Stage 0, representing an organisation lacking digital data management initiatives, and culminates in Stage 5, signifying comprehensive leadership and mature data governance. The progression patterns of leadership and governance in the digital transformation of data management, based on descriptions from **sections 4.1-4.6**, are as follows. For dimensions like Data Acquisition, Documentation and Quality, Data Description and Representation, Data Dissemination and Sharing, and Data Repository Services and Preservation: Leadership typically begins to approve and support policy establishments by Stage 3. By Stages 4 and 5, leaders are more actively engaged in governance activities, with improved policies and regular evaluation guides in place. Influenced by leadership, staff across all levels actively participate in activities and trust the tools and skills related to data management from Stage 3 onwards. Policies concerning data management are typically established at the department level or for ad-hoc projects by Stage 2. By Stage 3, these policies are well-defined across the entire organisation. Quality quantitative goals related to these policies are established by Stage 4, with evaluations for continuous improvement introduced by Stage 5. Steering committees specific to each domain are usually considered in

Stage 3, formed by Stage 4, and quantitative metrics like KPIs and SLAs for monitoring data management performance are defined by Stage 4. For dimensions of Data Analysis, Budget, and Operational Infrastructure: Leaders engage in policy establishments from Stage 2. By Stage 4, staff are fully involved in data analytics, considering budget allocations, and applying data management infrastructures. Certain departments, like IT, might define some policies, but all policies related to data analytics, budget allocation, and operational infrastructure are established organisation-wide by Stage 4. Stage 5 introduces regular evaluations for enhancing analytic capabilities and the efficacy of budget allocation and tools/techniques for managing data. The utilisation of data management infrastructures begins being monitored by steering committees in Stage 2, with quantitative metrics introduced by Stage 3 — this is earlier compared to other governance activities.

Regarding the contribution of this research, numerous Capability Maturity Models (CMMs) or Stage Models already exist. However, three key observations emerge from our investigation: *1) Few CMMs from the past decade address digital transformation in data management. 2) CMMs specifically discussing both leadership and governance within the context of digital transformation in data management are scarce.3)While there are limited papers about leadership in digital transformation concerning data management, they neither cover the complete data lifecycle (from data acquisition to data visualization) nor discuss data governance comprehensively.* Many CMMs on data management only touch upon leadership and governance tangentially, which, in the view of this study's authors, is inadequate. Leadership and governance extend beyond mere top management awareness. These realms encompass the broad dissemination of digital transformation concepts throughout the organisation, comprehension of evolving digital tools, support for policy formulation and execution, and setting both immediate and long-term organisational objectives to guide digital transformation in data management, among other roles. Therefore, this research advocates for a deeper and more nuanced understanding of leadership and governance, deeply rooted in the data lifecycle, aiming to offer precise and actionable insights for digital transformation. The distinctive contributions of this paper include: *1) The introduction of a unique Stage Model for leadership and governance in the digital transformation of data management, encapsulating the entire spectrum of contemporary data lifecycles. 2) The presentation of a comprehensive Stage Model that serves as a roadmap for organisations, enabling them to ascertain their current standing in data management and navigate towards future growth.*

Regarding limitations and recommendations, while this research discusses leadership and data governance broadly, approaches to data management can differ across industries. Thus, it is suggested that the LGSM be adapted and refined for specific sectors, such as its application to research data management within academia. A detailed case study is advocated for subsequent research. Discussions regarding the weighting and ranking of LGSM's dimensions in various industries would also be beneficial. Moreover, the authors suggest that subsequent research on CMMs should either retain these dimensions or further refine them. Such an approach accentuates the progression within each stage, enabling users to clearly recognise both the strengths and limitations of their current stance.

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