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To James and Bazz

UMEÅ UNIVERSITET

DATA LIQUIDITY AND DATA FRICTION

Governing the Contingencies of Data in Motion

Panagiota Koukouvinou

Institution eller motsvarande
Umeå 2025

Dissertation for PhD

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Abstract

With the growing influence of data-driven technologies and Artificial Intelligence (AI) across industries, questions of data governance have become a central concern. As organizations embark on digital transformation initiatives to enhance their operations, services, and strategies through AI, the effective management of data has become a key condition for success. However, most data governance frameworks focus on technical aspects, overlooking the everyday work that makes data usable, meaningful, and trustworthy. Based on qualitative research in Swedish forestry, this study traces how data are produced, interpreted, and moved across the sector. To capture this process, I introduce the concept of *data journeys*, the paths along which data move, transform, and sometimes get stuck as they encounter tools, people, and organizational boundaries. What enables data movement is *data liquidity*, the capacity of data to be reused or recombined across contexts without losing their interpretive integrity. Data liquidity, however, is not a given – it depends on a variety of socio-technical arrangements. When these fail, data friction emerges. *Data friction* refers to the obstacles that slow or block data movement. Yet data friction is not inherently negative. In forestry, where data must often be interpreted with care and based on ecological expertise, data friction can be productive. It draws attention to data ambiguity, prevents unwanted data sharing, and protects against context loss. This leads to the central argument of the dissertation: data governance is not just about enabling flow, it is also about negotiating the tensions between data liquidity and data friction. Effective data governance involves knowing when to enable data movement and when to slow it down.

Based on the above, the dissertation makes three contributions. First, it moves beyond traditional assumptions of data governance as a matter of formal control, data quality, or compliance. It does so by conceptualizing data governance as a practice-based, socio-technical process, enacted through the everyday efforts of making data usable across systems and contexts. Second, it develops the concepts of data journeys, data liquidity, and data friction to trace how data governance unfolds in motion. In doing so, it highlights the socio-technical frictions that shape data work in practice. These data frictions often reveal where the limitations of data liquidity are and what work is required to restore it. Third, the dissertation challenges the assumption that data friction is inherently problematic. It shows that data friction can be protective, reflective, and even productive.

Keywords: data governance, data work, data liquidity, data journeys, practice-based view, data friction.

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I would be lying if I didn’t admit that this is the part I have been most looking forward to writing. They say a PhD is a lonely journey—and in many ways, it is. But I have been fortunate to have so many people who made this path less lonely and far more enjoyable. I will try to do them justice here.

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/ Peggy

Uppsala, September 2025

Preface

This dissertation consists of a cover manuscript and four research papers. The purpose of the cover chapter is to position and explore the evolving role of data governance as a socio-technical practice, with a particular focus on how it shapes data work practices. It offers a conceptual and analytical framing that connects and contextualizes the contributions of the individual papers, examining how data governance is enacted and negotiated in practice. The four research papers, presented after the cover manuscript, each address distinct but interconnected aspects of data governance. The research papers are presented in the cover manuscript, in the following order:

Paper 1: Koukouvinou, P., & Holmström, J. (2024). AI management beyond myth and hype: A systematic review and synthesis of the literature. *Pacific Asia Journal of the Association for Information Systems*, *16*(2). https://doi.org/10.17705/1pais.16201.

Paper 2: Koukouvinou, P., Simbi, N., & Holmström, J. (2023). Managing unbounded digital transformation: Exploring the role of tensions in a digital transformation initiative in the forestry industry. *Information Technology & People*, *36*(8), 43-68. https://doi.org/10.1108/ITP-03-2020-0106.

Paper 3: Koukouvinou, P., Carroll, N., & Holmström, J. (2025). Lost in transformation: Navigating the challenges of data-driven sustainability when you can’t see the forest for the trees (Under review in an international journal).

Paper 4: Koukouvinou, P., Holmström, J., & Henfridsson, O. (2025). AI at work: Mapping data journeys for ai use in the forestry industry. (Manuscript).

1.Introduction

1.1 Motivation: The Story Behind the Thesis

In recent decades, digital technologies have reshaped industries, altering how organizations are structured, how they compete, and how they deliver value. Central to this digital revolution is Artificial Intelligence (AI), increasingly recognized not merely as a tool, but also as an enabler of digital transformation (Iansiti and Lakhani, 2020; Holmström, 2022; Koukouvinou and Holmström, 2024). AI's impact extends far beyond simple task automation; it is fundamentally reshaping how value is created. By enabling organizations to rethink their business processes (Tarafdar et al., 2019; Baiyere et al., 2020), AI supports operations that are more efficient, agile, and responsive (Coombs et al., 2020; Sandberg et al., 2020; Berente et al., 2021; Hanelt et al., 2025). It assists in the redesign of products (Huang et al., 2019) and transforms the ways in which services are delivered (Shollo et al., 2022; Coombs et al., 2020). Moreover, AI has emerged as a catalyst for innovation management, driving new forms of experimentation and data-driven creativity (Iansiti and Lakhani, 2020; Mariani et al., 2023; Kakatkar et al., 2020). Beyond improving organizational operations, AI is reshaping the nature of decision-making through increased predictive power, analytical insights, and adaptive intelligence (Kelly, 2017; von Krogh, 2018; Berente et al., 2021; Mikalef and Gupta, 2021). Interestingly, AI is not only changing what organizations do, but also how they do it. It is challenging traditional roles by redefining the distribution of expertise and control (Kellogg et al., 2020; Jarrahi et al., 2021; Waardenburg et al., 2021; van den Broek, 2021) and transforming knowledge production and organizational practices (Orlikowski et al., 2016; Jonsson et al., 2018; Pachidi et al., 2021; van den Broek, 2021; Lebovitz et al., 2021; Aaltonen and Stelmaszak, 2023; Sundberg and Holmström, 2024).

Motivated by these developments, my initial research interest was to understand how AI enables digital transformation of work practices in organizations, particularly in traditional industries. My investigative context, the forestry industry, is often characterized by legacy practices that result in slower technological adoption (Koukouvinou et al., 2023; Rantala et al., 2022). To explore this phenomenon, I conducted two case studies: one at the Cluster of Forest Technology and another at Holmen Forest. Although the Cluster of Forest Technology pursued a clear digital transformation initiative, a different narrative emerged at Holmen Forest (hereafter Holmen). As I became more closely involved with the company during the second year of my doctoral program and followed how events unfolded (Charmaz, 2006), the research took an unexpected turn. The empirical observations revealed a more complex—and to me, more compelling—reality than I had initially anticipated. Gradually, these insights reshaped the direction of my research, helping me refine both its focus and objectives. While AI-driven initiatives to transform practices and value propositions seemed to dominate the narrative at first, I came to realize this was only part of the picture. Different levels of complexity were shaping the pace, process, and outcomes of digital transformation in ways I had not expected. This realization pushed me to look more deeply at the fundamental building blocks of digital transformation. To explain why this case does not align with conventional digital transformation narratives, I will begin with an overview of the digital transformation literature. This also clarifies why digital transformation itself did not remain the central phenomenon of my work.

Transformation entails change, but not all changes can be classified as transformation (Aldrich, 1999). Transformation is a distinct process which, as Singh and Hess (2017) suggest, in an organizational context, involves the critical actions that an organization must undertake when faced with emerging digital technologies. Thus, transformations often introduce significant discontinuities into an organization's operations, potentially disrupting its goals, boundaries, and activities (Aldrich, 1999). Digital transformation is widely regarded as a strategic and profound organizational change (Vial, 2019; Wessel et al., 2021; Kaganer et al., 2023; Piccoli et al., 2024). This is what Besson and Rowe (2012) and Baiyere et al. (2020) call "*deep structural change*" and it is *"triggered and shaped by the widespread diffusion of digital technologies"* (Hanelt et al., 2021, p. 1160). The cumulative body of knowledge on digital transformation emphasizes several key themes, which I briefly outline below.

First, scholars point out that the technologies driving digital transformation introduce new properties such as generativity and malleability, which have implications for the design and governance

(Kaganer et al., 2023; Baiyere et al., 2023; Koukouvinou et al., 2023; Piccoli et al., 2024). Second, a body of knowledge explores the strategies that organizations put in place to identify and leverage opportunities offered by digital technologies to achieve competitive advantages (Bharadwaj et al., 2013; Matt et al., 2015; Kane et al., 2015; Sebastian et al., 2020; Baiyere et al., 2020). Third, the literature explores the outcomes of digital transformation. This takes the form of radical changes that lead to cultural and structural reconfiguration (Gurbaxani and Dunkle, 2019), shifts in value propositions that reshape organizational identity (Hinings et al., 2018; Wessel et al., 2021; Westergren et al., 2024), and the evolution of mindsets needed to manage digital transformation (Koukouvinou et al., 2023; Kaganer et al., 2023; Amadoru et al., 2025).

Although there were evident shifts in mindset resulting from gradual learning through AI exploration (Neeley and Leonardi, 2022), no significant strategic changes in value propositions or organizational identity took place (see Wessel et al., 2021). The organization initiated projects to explore AI's potential for enabling organizational transformation, but domain experts surfaced a different set of concerns. These concerns were not centered on AI's strategic promise but were deeply embedded in data-related challenges within daily work practices specifically; ongoing questions about how data should be managed, who should use them, and under what conditions (Khatri and Brown, 2010; Abraham et al., 2019). Looking closer, I realized that these concerns reflect the common view of data governance as "*a companywide framework for assigning decision-related rights and duties in order to be able to adequately handle data as a company asset*"(Otto, 2011b, p.47). Yet these issues extended beyond conventional notions of data quality management that focus on merely resolving technical issues (Lee, 2003; Moges et al., 2013; Jiang et al., 2021). They also encompassed matters of how practitioners work with, interpret, and rely on data in practice, what is called data work (Parmiggiani et al., 2022; Kostis et al., 2024). These observations prompted a critical reorientation in my research. I shifted focus from digital transformation to a more specific inquiry into how data are governed in practice, and how data can be usable for further supporting organizational change.

Zooming into data governance is crucial, particularly in light of the recognition that "*algorithms without data are just mathematical fiction*"

(Kallinikos and Constantiou, 2015, p. 73). As Monteiro (2022, p. 11) puts it, "*data, increasingly, are the phenomenon,"* pointing to how data do not simply represent organizational activities, but are themselves part of how those activities are constituted. This has direct implications for organizational strategy (Constantiou and Kallinikos, 2015; van den Broek, 2025), business operations (Günther et al., 2017), competitive advantage (Abbasi et al., 2016), and digital agility (Grover, 2022). An emergent issue is what is governed in the first place, rather than how data are governed. Data are dynamic in nature: continuously editable (Alaimo and Kallinikos, 2024; Kallinikos et al., 2013), mutable, and imbued with representational flexibility (Mikalsen and Monteiro, 2021). As a medium of signification, data are revisable and expandable, making them highly amenable to reuse and recombination (Ekbia et al., 2009; Jones, 2019; Alaimo et al., 2020). Data are also portable, moving across contexts, time, platforms, and organizational boundaries (Leonelli, 2019; Leonelli and Tempini, 2020; Alaimo and Kallinikos, 2024) – attributes that generate data uncertainty (Mikalsen and Monteiro, 2021). This portability enables recontextualization and transformation, allowing new meanings and stories to be created beyond the original purpose or origin of the data (Leonelli and Tempini, 2020; Monteiro and Parmiggiani, 2019). Therefore, assuming that data are a neutral "given" (Gitelman, 2013), or objective reflection of reality, is a fallacy (Burton-Jones and Grange, 2013; Mikalsen and Monteiro, 2021; Monteiro, 2022). What enables data to move and be reused across contexts is often referred to as *data liquidity*, a condition shaped by the data work, infrastructure, and governance that make data usable. It is the challenge of data's portability and ambiguity on one hand, and the formalized and situated practices to make data usable, interpretable, and meaningful on the other, that anchors my research focus.

Still, data liquidity is not automatic or a given. It is continually tested and shaped by data frictions, the obstacles that arise as data traverse time, space, and organizational boundaries (Edwards, 2010; Edwards et al., 2011; Bates et al., 2016; Aula, 2019). These frictions are signals of deeper misalignments in socio-technical arrangements. They surface where meanings do not align, data formats are insufficient, or data practices become hidden. My research is anchored in this tension between the fluid promise of data and the frictions that bound them. It is here, in the space between movement and resistance, that the work of data governance is done and where transformation either unfolds or unravels. This realization leads to the central argument of the dissertation, namely that effective data governance is not simply about maximizing flow or eliminating obstacles, but also about negotiating the tension between data liquidity and data friction. The dissertation demonstrates that data governance in practice involves knowing when to accelerate data liquidity and when to preserve data friction. By placing this negotiation at the core of the analysis, I shift the view of data governance from static data governance frameworks toward dynamic, socio-technical practices. This perspective also informs how I approach the study empirically and methodologically.

Against this backdrop, the motivation and trajectory of this thesis is phenomenon-driven, as I engage in a dialogue with my empirical setting (Fisher et al., 2021; Monteiro et al., 2022; Gkeredakis and Constantinides, 2019; Schwarz and Stensaker, 2016). The phenomenon-driven theorizing asks how particular assumptions have come to shape everyday practices, why these assumptions may need to be questioned, and how their consequences are manifested in organizational life (see section 4, Research Design, for further elaboration).

1.2 Problem Statement and Research Objectives

As I moved from empirical setting to theory, I began examining how the literature conceptualizes data governance. Considering that data are becoming increasingly embedded in all aspects of social and economic life, understanding how *"organizations [become] immersed in the management of data and by data"* (Alaimo and Kallinikos, 2020, p. 19) has emerged as a central concern for the Information Systems (IS) field. It has become clear that data governance is an important concern for organizations navigating transformations and broader societal challenges (Davidson et al., 2023). For over a decade, scholars have referred to a "relative winter," a period marked by limited theoretical coherence, lack of empirical insights, and absence of cumulative progress (Otto, 2011a; Abraham et al., 2019; Walsh et al., 2022). These limitations highlight the need to revisit the assumptions underpinning existing scholarship. In efforts to approach this literature, I was guided by Alvesson's and Sandberg's (2011) call to move beyond conventional "gap-spotting," toward problematization. Problematizing dominant assumptions about how data governance has evolved, opened for a different way of seeing it as enacted in practice and situated within organizational contexts. Based on this review (presented in Section 2.2), I identified three interrelated problems that require further attention.

First, definitions of data governance are inconsistent (Abraham et al., 2019; Benfeldt et al., 2020). This lack of conceptual clarity makes it difficult for scholars to build cumulative insights. Second, current dominant perspectives continue to frame data governance as either an extension of IT governance (Weill and Ross, 2004; Khatri and Brown, 2010; Abraham et al., 2019) or a mechanism for ensuring data quality (Wang and Strong, 1996; Kwon and Johnson, 2013). Although these approaches have provided valuable foundations, they reduce data governance to formal structures, control mechanisms, and technical standards. This framing tends to treat data as stable objects to be secured, standardized, and optimized, neglecting that data are situated, mutable, and socially constructed (Bowker and Star, 1999; Parmiggiani et al., 2022; Monteiro, 2022). Third, research approaches data governance as a system of constraints and compliance, focusing on what organizations must prevent, regulate, or secure. This view overlooks that data governance is also an ongoing process that makes data mobile and usable across contexts.

To address these issues, I reconceptualize data governance in terms of the situated practices through which data are produced, circulated, and reused (Parmiggiani et al., 2022; Parmiggiani and Grisot, 2020; Parmiggiani et al., 2024). In this thesis, I use the concepts of data liquidity and data friction as a vocabulary for thinking about data in motion. Data liquidity refers to the conditions that allow data to travel across contexts (Piccoli et al., 2022), while data friction highlights the moments where the movement was stalled, reshaped or became productive (Bates, 2018). By tracing these dynamics through the concept of data journeys, we can see how data governance unfolds as an emergent and negotiated process of data work.

From this foundation, the dissertation addresses the following research question:

How is data liquidity shaped through the negotiation of data frictions and everyday data work in organizational contexts?

The aim is to contribute to a more grounded understanding of data governance by explaining what data liquidity and data friction are, how they are interrelated, and how and why they emerge in organizational contexts (Gregor, 2006). The contributions are therefore conceptual, in offering a reframing of data governance; empirical, in showing how these dynamics unfold in practice; and lastly, methodological, in advancing data journeys as a way to trace data work and reveal the negotiations that shape data movement.

1.3 Research Approach and Contributions

This dissertation is based on a doctoral research project consisting of four interrelated papers, Papers 1–4. Each contributes to the central research question: *How is data liquidity shaped through the negotiation of data frictions and everyday data work in organizational contexts?*

Paper 1 presents a systematic literature review that synthesizes existing research on AI from a socio-technical perspective, thereby offering a conceptual compass to navigate the fragmented field of AI. Paper 2 examines a digital transformation initiative in forestry and shows that tensions around knowledge flows, collaboration, and competition represent the challenges that organizations face when managing digital transformation. Paper 3 highlights two central challenges: the "temporality paradox, "which arises from the differing rhythms of forestry practices and data analytics practices, and the "exploration loop", which reveals how the lack of concrete data strategy implementation can stall digital initiatives. Paper 4 brings everyday data work to the forefront of analysis by tracing data journeys, the ways in which data are produced, circulated, stalled, and reinterpreted across settings, and shows how data governance is enacted in practice.

Taken together, the four studies demonstrate that data governance is a negotiated process shaped by data work practices. Conceptually, the dissertation develops the vocabulary of data liquidity, data friction, and data journeys to explain how data governance emerges through negotiations of movement and stability. It also shows why these negotiations matter for organizations dealing with uncertainty, meaning, and trust. Methodologically, it mobilizes the approach of data journeys to trace how data travel across contexts, showing why these movements are central to understanding data governance in action. On the empirical side, it provides novel insights into how data governance unfolds in forestry, illustrating why the often invisible data work that shapes both data liquidity and data friction is an important part of organizational work.

1.4 Thesis Structure

This dissertation consists of four research papers and a cover manuscript. The cover manuscript is organized into nine chapters.

Chapter 1 sets the stage for the dissertation by linking it to ongoing debates on data governance. It shows how data have become essential for organizations, introduces the motivation behind the study, and presents the main objectives. The chapter concludes by posing the research question that guides the dissertation as a whole.

Chapter 2 describes and problematizes prior literature on data governance. By synthesizing the literature, it clarifies how data governance has been defined and unpacks its conceptual underpinnings. The chapter also examines how data work practices are addressed in existing research.

Chapter 3 synthesizes the theoretical approaches of the dissertation, introducing the concepts of data journeys, data liquidity, data friction, and practice-based theory. It also explains how these concepts guide the way data governance is analysed.

Chapter 4 details the research design, elaborates on the interpretive foundations of the study, reflects on the use of grounded theory, and explains the evolving logic of a qualitative case study approach. It shows how the phenomenon-driven approach guided methodological choices and how these informed the findings. This chapter also describes the approach to data analysis, showing how coding, comparison, and theoretical development unfolded throughout the thesis work.

Chapter 5 offers ethical and methodological reflections. It discusses the researcher's position, the ethical dilemmas that came up during interviews and fieldwork, and how issues of access and confidentiality were managed. The chapter also reflects on the methodological choices made and how they shaped the research.

Chapter 6 describes the Swedish forestry sector. It outlines the sector's organizational structures, data infrastructures, and data practices, and explains why this context is compelling for studying how data governance unfolds in practice.

Chapter 7 summarizes the four appended papers. It outlines the research questions, methods, and key empirical insights of each paper, and clarifies the author's specific contributions to each paper. The chapter also shows how the papers build the overall argument of the dissertation and address the central research question.

Chapter 8 synthesizes the main findings of the dissertation and discusses how they advance the understanding of data governance. It elaborates on the theoretical contributions to IS research, reflects on practical implications for managers and organizations, and considers how the findings connect to broader debates in the field.

Chapter 9 discusses the limitations of the dissertation and suggests topics for future research. The chapter concludes with my reflections on possible directions for future research.

2. Data Governance: Old Wine in New Bottles?

This chapter offers a synthesis of data governance literature to position the phenomenon within the broader IS discourse. First, I elaborate on views of data. Following this synthesis, I highlight key emergent issues and challenges facing data governance scholarship. Paper 4 provides a review of different perspectives on data governance. Here, however, the focus is on presenting its evolution within IS research and highlighting the challenges of how data are conceptualized and governed in organizational contexts.

To ground this discussion, it is useful to briefly clarify the distinction often made between data governance and data management. Data governance encompasses decisions on managing a data asset, whereas data management involves the operational implementation of those decisions (Khatri and Brown, 2010; Abraham et al., 2019). However, this dissertation departs from conventional distinctions that treat data governance as a formal overlay to data management. Focusing on data governance rather than data management is not a matter of hierarchy or function, but of analytical perspective. It allows me to investigate issues of how accountability and meaning are negotiated in data practices, and explore how these negotiations shape the conditions under which data become usable, trusted, and mobile across settings.

2.1 A Synthesis of Data Governance Research in Information Systems

From the first time I engaged with data governance literature, it became clear to me that the field was marked by both persistent conceptual tensions and practical difficulties. The definitions vary (Otto, 2011a; Benfeldt et al., 2020), theoretical foundations are fragmented (Abraham et al., 2019), and assumptions about what data governance is, and equally importantly, whom it serves, differ widely.

I undertook this review to make sense of these inconsistencies and build a more grounded understanding of the field. The aim was to explore what data governance is and examine how its meanings, purposes, and underlying assumptions have shifted over time. In this process, I gave attention to how data have been framed, valued, and mobilized, and how these framings have shaped practices of data governance. Tracing this definitional trajectory exposed assumptions, tensions, and gaps (Alvesson and Sandberg, 2020).

The review followed a phenomenon-driven problematization approach (Monteiro et al., 2022). This meant engaging critically with the literature to question existing perspectives, rather than simply describing them. This made it possible to move beyond definitions, toward identifying the conceptual patterns and shifts that mark the field's development. Through this analysis, three waves in the historical evolution of data governance emerged. The first, *The Emergent Foundations of Data Governance*, established technical approaches centered on efficiency, storage, and control. The second, *Data Governance as a Strategic Resource for Managing and Organizing*, indicated a transition towards perceiving data as an enterprise resource. The third wave*, Evolving Toward Socio-technical Data Governance,* highlighted the relational and interpretive nature of data and the need for adaptive, flexible data governance models. I now turn to elaborating on these waves.

First Wave (since the 1960s): The Emergent Foundations of Data Governance

In the mid-1960s, organizations began adopting electronic data processing to automate core administrative tasks such as payroll, billing, and record-keeping (see also Bergin and Haigh, 2009; Alaimo and Kallinikos, 2022). The main goal was to turn manual processes into machine-readable formats in order to enhance operational efficiency (Gillenson, 1985). Following the growth of data volumes in the 1970s and 1980s, there was increased interest in the adoption of database management systems and in operations as a foundational solution for managing organizational data (Blair, 1984; Gillenson, 1985, Goodhue et al.,1988).

This focus on data management emphasizes data model design (Chen, 1976; Lee et al., 1997; Hirschheim et al., 1995), availability, consistency, and reuse within specific systems (Aiken et al., 2013; see also the review by Legner et al., 2020, on the three phases of data management[1]).

During this period, data management was handled from a siloed, single-function perspective, with data administration restricted to managing individual database systems (Aiken et al., 2013). Early studies showed and criticized that although these systems enhanced efficiency, the absence of integration and managerial commitment often limited their long-term organizational impact (Lederer and Sethi, 1988). The rise of shared databases around this time, raised concerns of "*Who owns the data? In what form should it be stored? Who should be allowed to access it?*" (Bergin and Haigh, 2009, p.33). In this first wave, the dominant view of data was still factual. This perspective was described by Blair (1984) who emphasized that data are objective facts, derived from a singular, verifiable truth.

This period can be seen as the *agenda-seeking* phase of data governance, where technical control dominated and data were treated as enablers of automation rather than shared enterprise resources. As outlined in Table 1, this approach brought operational efficiency but also exposed significant gaps in coordination, ownership, and standardization, laying the ground for more structured and enterprise-wide data governance frameworks in subsequent phases.

[1] It should be noted that the three waves are structured around the *logics* of data governance and do not follow a strictly chronological order. This means that some more recent studies are situated in earlier waves because they continue to refine or extend previous work. For example, Legner et al. (2020) is situated in the first wave as it revisits and systematizes the phases of data management. Another example is Timmerman et al. (2023), which is placed in the second wave because it criticizes and expands on the tradition of data quality management.

Table 1. Representation of data governance waves.

Wave	Focus and Trajectory	Role of Data	Examples of Relevant Literature	Implications in the Field
The Emergent Foundations of Data Governance	**Agenda-seeking:** Emphasis on data processing, storage, and retrieval; siloed data management within specific systems; efficiency and automation within organizational functions.	Objective facts enabling process automation and system efficiency; treated mainly as technical assets managed locally.	Gillenson (1985); Goodhue et al. (1988); Bergin and Haigh (2009); Lederer and Sethi (1988); Chen (1976); Aiken et al. (2013); Blair (1984); Lee et al. (1997); Hirschheim et al. (1995).	Established technical foundations for data storage and management, but issues of data ownership and coordination across systems were exposed.
Data Governance as a Strategic Resource for Managing and Organizing	**Agenda-forming:** Enterprise-level integration and strategic alignment; development of (IT) governance frameworks; focus on decision rights, data quality, and standardization.	Viewed as enterprise assets.	Weber et al. (2009); Khatri and Brown (2010); Lee (2003); Goodhue et al. (1992); Dawes (1996); Levitin and Redman (1998); Grover and Teng (1991); Jain et al. (1998); Segars and Grover (1998); Wang and Strong (1996); Wang (1998); Shanks (1997); Strong et al.	Formalized data governance and management structures and methods (e.g., strategic data planning, data resource management); positioned data governance as a managerial concern; surfaced challenges in implementation and abstraction.

			(1997), Hoffer et al. (1989); Lederer and Sethi (1991); Periasamy and Feeny (1997); Cichy and Rass (2019); Otto and Sadiq (2013); Timmerman et al. (2023), Wende and Otto (2007), Otto (2011a, b); Lee et al. (2014); Sambamurthy and Zmud (1990)	
Evolving Toward Socio-technical Data Governance	**Agenda-expanding:** Recognizes the relational and context-sensitive nature of data; data governance is a dynamic, ongoing, and tied to organizational sense-making.	Mutable, interpretive, and context-depended resources; data seen as ontologically unstable and epistemologically constructed	Alaimo and Kallinikos (2020, 2022, 2024); Constantiou and Kallinikos (2015); Aaltonen et al. (2021); Monteiro and Parmiggiani (2019); Parmiggiani et al. (2022); Vassilakopoulou et al. (2019); Paparova et al. (2023); Aaltonen and Stelmaszak (2024); Xu et al. (2024; 2025), Zhang	Calls for adaptive data governance frameworks that can manage data movement across different contexts and recognize their socio-technical embeddedness.

			et al. (2024); Micheli et al. (2020); Paparova et al. (2023), Black et al. (2023); Thompson et al. (2015); Benfeldt et al. (2020); Benfeldt and Persson (2025); Parmiggiani and Grisot (2020)	

Second Wave (since the 1980s): Data Governance as a Strategic Resource for Managing and Organizing

Beginning in the 1980s, data were increasingly framed as a strategic resource for organizations. This growing interest further highlighted the need for data responsibility. As a result, roles such as "data administrator" began to emerge. Such roles, however, were often subordinated within IT hierarchies and lacked the authority to address issues like data duplication or inconsistency across organizational units (Blair, 1984; Bergin and Haigh, 2009).

In the late 1990s, data were still widely perceived as raw facts that, when structured and contextualized, became information and, ultimately, knowledge (see also Blair, 1984). This linear hierarchy of data, information, and knowledge was related to the idea that "data are a prerequisite for information, and information is a prerequisite for knowledge" (Tuomi, 1999, p. 104). Tuomi (1999) challenged this traditional view by reversing the hierarchy. He argued that data do not naturally exist as objective raw facts but rather emerge only after information is structured and given meaning. In his view, it is the interpretation and contextualization, i.e., information that precedes and defines what is recognized as data.

Similarly, scholars such as Levitin and Redman (1998) stressed the need for managing data in different ways than other resources. One of the central developments during this phase was that the emphasis turned toward enterprise-wide data integration. Unlike the first wave, organizations now sought to unify their data environments. The adoption of enterprise resource planning (ERP) systems and computer-integrated manufacturing (CIM) highlighted the need for shared data models that supported cross-functional workflows (Grover and Teng, 1991; Ravindran, 1986). These technologies required consistent data structures pressuring organizations to move from localized data administration to centralized coordination.

As data became increasingly integral to business operations, the limitations of traditional data administration were exposed. The work of Goodhue et al. (1992) was essential in illustrating how inconsistent data definitions and fragmented schemas obstructed enterprise-wide coordination. Their study highlighted the challenges that organizations faced when attempting to integrate data across functional boundaries. In response, new frameworks like strategic data planning (SDP) and data resource management (DRM) emerged (Jain et al., 1998), aiming to align data management more closely with organizational strategy (Goodhue et al., 1988; Jain et al., 1998). SDP, as discussed by Goodhue et al. (1992) and Shanks (1997), offered a structured, top-down planning methodology focused on modelling enterprise data. Its purpose is to create a shared data architecture that supports integrated systems and aligns data use with business goals.

However, numerous studies reported difficulties in implementing SDP due to a lack of top management support and the often abstract, impractical outputs of SDP (Beynon-Davies, 1994; Goodhue et al., 1992; Hoffer et al., 1989; Lederer and Sethi, 1991; Periasamy and Feeny, 1997). Yet, importantly, these studies became the foundation for data governance by introducing principles of alignment, integration, and organizational planning. Jain et al. (1998) coined the term DRM and identified mechanisms for improved data management, including organizational planning, policy development, and data infrastructure. This broadened the scope of data governance by viewing data as a strategic resource. Wang (1998) extended this thinking by applying total quality management (TQM) principles to data, promoting evaluation and control practices. This shift toward treating data as strategic organizational resources introduced new conceptual and operational challenges. In the early 2000s, two dominant traditions shaped data governance discourse, namely the rise of data quality as a critical concern and the formalization of IT governance as a managerial discipline. The first views data governance primarily as a mechanism for ensuring data quality, whereas the second positions it as a framework for exercising strategic control over data assets (Zhang et al., 2022; Benfeldt et al., 2020). In what follows, I present the main threads of these dominant traditions.

Data Governance Roots in Data Quality Management: Data quality has been regarded as the core of data governance (Weber et al., 2009; Otto, 2011a; Jiang et al., 2021). From this view, data governance is conceptualized as a technical mechanism for resolving problems such as inconsistency, inaccuracy, and lack of reliability (Lee, 2003; Panian, 2010; Moges et al., 2013; Jiang et al., 2021). Specifically, the literature explores multiple dimensions of data quality, including accuracy, timeliness, precision, objectivity, completeness, consistency, preventability, and relevance (Wand and Wang, 1996; Cappiello et al., 2003; Lee and Strong, 2003;Cichy and Rass, 2019; Otto and Sadiq, 2013; Timmerman et al., 2023).

A common definition of data quality is the "fitness of data for use" by consumers (Wang and Strong,1996). However, what is perceived as "fit" is context-dependent as data considered suitable for one purpose may be inadequate for another (Wand and Wang, 1996; Strong et al., 1997). More recent work, such as Timmerman et al. (2023), elaborate and criticize the assumption of "fitness of use." The authors argue that data quality is not fixed in the data themselves but emerges through situated practices that define what counts as useful and credible in a given organizational context. Building on this, scholars have expanded the conversation to include concerns such as the risk of data mistrust (Zhang et al., 2022). Aaltonen and Stelmaszak (2024), for example, show that attempts to improve data quality through tighter monitoring may backfire, as employees adapt their behaviors in ways that end up distorting the data. From this, we can extrapolate that data quality depends more on how people engage with and trust data. Other concerns identified are organizational maturity, security and compliance considerations (Kwon and Johnson, 2013), and challenges in data quality assessment techniques (Zhang et al., 2019).

Although this aspect of data governance has advanced our understanding of data quality, it also exposes several important limitations. Data governance frameworks that overemphasize technical attributes often conceptualize data quality as a fixed and measurable property (cf. Xu et al., 2024). In these cases, data quality can be sustained by managerial controls that often include strict rules and procedures (Zhang et al., 2019). These data governance approaches typically assume that users understand the full context of the data – how they were collected, for what purpose, how they have been reused, and under what data governance constraints. Furthermore, such frameworks lack the flexibility required to accommodate emergent, unstructured, and cross-contextual data sources (ibid.). As a result, this approach often falls short in addressing the socio-technical complexity and dynamic nature of contemporary data environments.

Recent research has begun to challenge traditional assumptions about what constitutes high-quality data. Xu et al. (2025) argue that the concept of "good data" is far from settled, as new technological and organizational dynamics prompt a rethinking of data quality criteria. For example, Mikalsen and Monteiro (2021) argue that data quality is not fixed but constructed through practice. Using well logs as an example, the authors present how experts must interpret, validate, and triangulate data, especially older or incomplete logs, to make them usable. This illustrates that data quality depends on the sociotechnical work of making data meaningful in context. This tension reflects a broader debate around defining quality in terms of usefulness. Dawes (1996) argues that information must be helpful to intended users or support the usefulness of other information products. At the organizational level, data governance is often difficult to justify unless it clearly delivers value, such as better data quality or a unified customer view (Otto, 2011a). Wende and Otto (2007) therefore suggest that a data quality strategy is required to align data management activities with business objectives.

Data Governance Roots in IT Governance: The second stream conceptualizes data governance as a resource control framework, drawing directly from IT governance models such as those proposed by Weill and

Ross (2004). Here, Sambamurthy's and Zmud's (1999) early work on the design of IT governance is especially relevant. The authors emphasized the need for establishing formal mechanisms to coordinate and control IT resources across the organization. Khatri and Brown (2010), drawing from the IT governance model, proposed a framework built around five key decision domains: data principles, data quality, metadata, data access, and data lifecycle. Later, Tallon et al. (2013) extended this logic by incorporating *information governance* as a distinct decision area. The authors defined this as "*a collection of capabilities or practices for the creation, capture, valuation, storage, usage, control, access, archival, and deletion of information over its life cycle"* (p. 142). Their contribution reinforced the idea that data governance shares significant conceptual and operational similarities with IT governance, particularly in its reliance on structural, processual, and relational governance mechanisms (Fadler et al., 2021). Structural mechanisms determine reporting structures, governance bodies, and accountabilities. Processual mechanisms address data management by improving data quality and supporting data sharing. As Abraham et al. (2019) state:

> *these mechanisms typically include: (i) a defined data strategy; (ii) organizational policies; (iii) technical and quality standards; (iv) operational processes; (v) formal procedures; (vi) legal and contractual arrangements; (vii) tools for assessing performance; (viii) systems for monitoring compliance; and (ix) protocols for addressing data-related issues. (p. 429)*

Lastly, relational mechanisms concern the allocation of roles and responsibilities, and the ways in which they facilitate interaction and collaboration between stakeholders (Abraham et al., 2019). Still, the data governance mechanisms discussed above assume formal procedures in terms of planning and action that are static and linear. For instance, Abraham et al. (2019) stressed that procedures are documented methods, techniques, and steps that should be followed. Vial (2023) follows the same logic and asserts that data governance benefits from alignment with the established IT governance tradition, calling it a "*same logic to a different object"* (p. 4). The resemblance lies in how both models are structured around formalized decision processes. However, Tallon et al. (2013) underscore that the rapid information growth requires governance approaches that take into consideration data and information alike.

Increasingly, IS scholars have critiqued this tradition, pointing out the risks of applying IT governance logics to data governance. They do so, by highlighting that data and IT artifacts differ in nature and therefore should not be treated in the same way. I discuss this further below in relation to the third wave of data governance.

Third Wave (2010s–): Evolving Toward Socio-technical Data Governance

In the early 2000s, data governance began to gain attention as a distinct concept (Parmiggiani and Grisot, 2020). In the 2010s, the increasing volume, velocity, and variety of both internal and external data renewed attention on the role of data in organizations (Chen et al., 2012; Chen et al., 2016). This shift brought both opportunities and challenges and forced organizations to reconsider how data were structured, managed, and governed. Data began to be treated as strategic assets central to shaping organizational strategy (Constantiou and Kallinikos, 2015; DalleMule and Davenport, 2017) and enabling innovation and growth (Mikalef et al., 2020; Alaimo et al., 2020; Alaimo and Aaltonen, 2023). This marked the beginning of an agenda-expanding era. The influence of data extended beyond operational optimization to drive new digital business models and reshape strategic thinking across industries (Wixom and Ross, 2017).

During this period, there was a constant effort to reconsider who should work with data. As it gradually became clear that data-related challenges could not be resolved by IT departments alone, the literature increasingly emphasized the need for overarching frameworks to guide how organizations analyze, manage, and govern data. This has included calls for the appointment of diverse roles to steer these efforts (Lee et al., 2014; Thompson et al., 2015; Benfeldt et al., 2020). The introduction of the Chief Data Officer (CDO), for example, represents a decisive shift. Unlike traditional data managers, CDOs are expected to be accountable for failures in addressing data challenges (Lee et al., 2014). Alongside this, data stewards, governance councils, and designated data owners have been tasked with maintaining quality, ensuring compliance, and overseeing risk (Dawes, 1996; Otto, 2011b; Tallon et al., 2013; Haug et al., 2021). More recent regulatory and ethical pressures have further expanded the governance landscape with roles such as Data Protection Officers, Chief Privacy Officers, Chief AI Officers, and Chief Ethics Officers

(Black et al., 2023). At the same time, this expansion of roles introduced new organizational challenges. Although these positions provide greater clarity in terms of accountability, align governance with regulatory expectations, and raise the visibility of data as a strategic concern, they also risk reinforcing silos, rigid hierarchies, and power asymmetries (Micheli et al., 2020; Thompson et al., 2015; Zhang et al., 2022). Scholars have observed that formal data governance frameworks issued at the top level often fail to reach or meaningfully engage operational staff, in part because the frameworks tend to be complex or abstract (Black et al., 2023). The emphasis on formally assigned responsibility may exclude those closest to the data: domain experts and everyday practitioners who play a central role in shaping their meaning and usefulness.

The emergence of these new roles was in many ways driven by the realization that data and IT could no longer be treated as interchangeable. Unlike IT systems, which are built for specific functions, data were increasingly understood as use-agnostic: open to reinterpretation, reuse, and circulation across different contexts without being depleted (Kallinikos et al., 2013; Alaimo and Kallinikos, 2020; 2024; Constantiou and Kallinikos, 2015). Scholars highlighted the ontological instability of data, including questions such as how they are produced, shaped, and made meaningful (Kallinikos et al., 2013; Alaimo et al., 2019; Aaltonen and Tempini, 2014; Aaltonen et al., 2021; Alaimo and Kallinikos, 2024). The epistemological understanding of data in terms of what they represent and how they convey meaning was increasingly stressed in the literature (Monteiro and Parmiggiani, 2019; Parmiggiani et al., 2022; Mikalsen and Monteiro, 2021; Monteiro, 2022; Aaltonen and Stelmaszak, 2024). This perspective resonates with the view of data as semiotic artifacts, cultural records, and instruments of knowing used to capture, represent, and act upon the world (Alaimo and Kallinikos, 2022). Benfeldt and Persson (2025) expand on this by explaining that data acquire value only through semiotic mediation as they are stabilized, classified, and made portable across contexts, or as symbols within specific organizational and regulatory arrangements. Through ongoing sense-making, data may transform into complex knowledge objects or economic assets, capable of moving across system and organizational boundaries (Vassilakopoulou et al., 2019; Aaltonen et al., 2021). This shift challenged long-held beliefs that data are referential (representing an external reality), objective (existing without the need for interpretation), equal (possible to analyze through the same methods), and foundational (serving as the basis of our worldview) (Jones, 2019).

Based on this growing awareness and interest, one might expect that data governance models would have evolved accordingly. However, dominant data governance approaches continue to treat data as stable and context-free, and their meaning as fixed. To address this, we need to shift the analytical lens toward data work. Thus, in the following section, I examine how data work unfolds in organizational contexts and why it is central to understanding data governance.

2.2 Data Work Practices

Let us zoom in on how data work reveals the enactment of data governance in practice. Data work has long been explored by scholars in IS research. Their studies have shown data practices like producing, processing, managing, and analyzing data (e.g., Bowker and Star, 1999). To grasp what data work entails, it is helpful to start with how scholars define it. Parmiggiani et al. (2022) describe data work as *"the extensive, complex, and ongoing tasks involved in finding and curating digital data...that happens before and during data science analytics in exploration and production"*. (p.3). This definition highlights important characteristics of data work. It shows that data are not simply discovered, but are shaped and made usable through the continuous efforts of those who handle them (Gitelman, 2013; Monteiro, 2022; Alaimo and Kallinikos, 2022; Bertelsen et al., 2024).

But when does data work begin? Data work starts well before data are analyzed, at the moment when categories and standards begin to shape what will count as data. As Bowker and Star (1999) argue, classification systems do not merely describe the world but actively construct what becomes visible and legitimate as data. In their view, "classification" refers to the categories, standards, and infrastructures through which organizations record and order information; choices that determine what will later be treated as "data" at all. Empirical studies confirm this. Data work begins with framing and selection practices, long before any analytical task takes place. This also raises questions about when data work ends. In fact, much of the literature suggests that it rarely has a clear endpoint. Data work is not a one-time activity. On the contrary, it is a *"unique form of work that consists of ongoing, convoluted and longitudinal practices"* (Parmiggiani et al., 2022, p. 749; see also Bertelsen et al., 2024) to manage their inherent ambiguity (Aaltonen et al., 2021). It often takes place through everyday actions that remain invisible or behind the scenes (Parmiggiani and Grisot, 2020; Parmiggiani et al., 2022; van den Broek, 2025). Data work involves iterative, skillful, and interpretive practices such as data production, preparation, validation, and algorithmic manipulation (Pine and Bossen, 2020; Møller et al., 2020; Parmiggiani et al., 2022; Mikalsen and Monteiro, 2021). Mikalsen and Monteiro (2021) further elaborate on this by identifying three interrelated modes of data work: accumulating (strengthening datasets through triangulation), reframing (challenging and reshaping models with new data), and prospecting (exploring and negotiating multiple interpretations). These practices illustrate the situated and interpretive nature of working with data in real-world settings.

Importantly, research underscores that data work is inherently collaborative (Grisot et al., 2019; Parmiggiani et al., 2022). For example, Grisot et al. (2019), in their study of data work among nurses in remote healthcare, identify three types of data work, shaped by how nurses "collect, make sense of, use, and act upon data" (p. 615). These practices included preparatory work, such as identifying relevant health concerns and selecting appropriate data for monitoring. They also involved continuous adjustment, where nurses reassessed and adapted monitoring strategies as the relevance of data changed. Finally, nurses engaged in fine-tuning questions, where they interacted with patients to elicit more specific or contextually meaningful data. Together, these practices show that data are actively shaped through interpretation, decision-making, and collaborative efforts embedded in everyday routines.

This brings up another question: who is actually performing data work? Although data science is often associated with technically skilled specialists, research shows that data work is far more distributed. It is also carried out by domain experts who generate, interpret, and adapt data during their day-to-day responsibilities (van den Broek et al., 2021). Data work is performed by a wide range of people (Pine and Bossen, 2020), from clerical staff and healthcare workers (Knudsen and Bertelsen, 2022; Grisot et al., 2019) to oil industry experts (Monteiro and Parmiggiani, 2019), police officers (Waardenburg et al., 2022b), and creative staff (Tyni et al., 2025). From this, we can see that what unites many forms of data work is a reliance on domain knowledge to make sense of the data. Domain expertise shapes how categories are applied, which distinctions are treated as legitimate, and how data are made actionable in organizational settings (Sundberg and Holmström, 2024; van den Broek, 2025).

Understanding the distributed and situated nature of data work is especially important in the context of AI, where concerns about what counts as "good data" are amplified. Recognizing this, boyd (2020) stresses that:

> *within the context of AI, we need to talk about what that data is, what it looks like, where it comes from, and what the nuances are. We need to tease out these issues in a sensible way so that we can better understand what makes data legitimate*. (p. 259)

Thus, recent studies highlight how the success of data work depends on the ability to generate and work with contextually meaningful data. In fact, data work is increasingly seen as the "organizing principle" of AI adoption (Kostis et al., 2024). Effective AI systems rely less on the sophistication of algorithms and more on the everyday labor that ensures data quality, relevance, and usefulness (Sambasivan et al., 2021). Expanding this view, Muldoon et al. (2024) emphasize that AI data work is not only distributed across roles but also shaped by institutional infrastructure that determines how, where, and by whom this essential labor is organized and carried out. This perspective directly intersects with current debates on data governance, shifting attention from formal frameworks to situated practices that make data actionable. Data governance, AI use, and data work are thus not separate domains, but interdependent practices (Jones, 2019; Vial, 2023).

3. Data Journeys between Data Liquidity and Data Friction

As discussed above (Section 2.2), data governance is grounded in data work, the everyday, often invisible practices through which data are produced, cleaned, organized, and made usable within specific organizational and infrastructural contexts (Parmiggiani et al., 2022). These dynamics became concrete in the empirical work, particularly in the findings of Paper 3 and Paper 4. Specifically, discussions with domain experts revealed recurring patterns in how data-related challenges manifested across organizations. These conversations highlighted issues such as a lack of timeliness and completeness (Cappiello et al., 2003; Lee and Strong, 2003), and limited accessibility (Wang and Strong, 1996), which often resulted in stalled data flows. Throughout our interactions, domain experts consistently described difficulties in making internal and external data useful. In particular, they referred to inconsistent data formats and standards, and a lack of "connected" data infrastructure, which reinforced data silos. These concerns raise broader questions: What enables data to move smoothly between contexts? And how can data governance support or hinder that movement?

To begin unpacking these issues, I turn to the concepts of data journeys, which trace how data move and change across settings (Leonelli and Tempini, 2020; Leonelli, 2019; Priego and Wareham, 2024), revealing the socio-technical work that makes data mobile. The idea of *following the data* builds on Appadurai's (1986) argument that to understand the value and significance of objects, we must "follow the things themselves." This perspective has inspired a growing body of research seeking to trace how data move and transform as they pass through various contexts. To help make sense of such data mobilities, scholars have developed a range of liquid-like metaphors, including data flows (Hoeyer et al., 2017), data streams (Dourish and Cruz, 2018), and data journeys (Bates et al., 2016; Leonelli and Tempini, 2020; Priego and Wareham, 2024; Beaulieu and Leonelli, 2022). However, these terms often imply that data move smoothly. Recent studies challenge this assumption, showing that data travel is uneven, negotiated, and frequently disrupted (see Kitchin et al., 2025).[2]

In my work, I draw on the concept of *data journeys*, which reflects the fragmented, labor-intensive, and often unpredictable paths that data take. Much like human journeys, data movement typically involves prior planning, multiple dependencies, and ongoing navigation through technical systems and social infrastructures (Leonelli, 2019; Edwards, 2010; Bates, 2018). It also involves uncertainty. Echoing Leonelli and Tempini (2020), I used data journeys as a means to *"consider and examine the relationship between different types of data structures (their physical characteristics as mutable objects) and data function (their perspective use as evidence)" (*p. 11). Here, we can see that the value of data depends not only on their initial form, but also on how they circulate across sites and systems. Following data journeys, therefore, draws attention to the multiple kinds of transformations that take place along the way. These may include technical changes, such as shifting formats or media (e.g., from analog to digital, or from a dataset to a visualization). They can also involve organizational and social changes, as data are reinterpreted, combined with other sources, or adapted to new purposes (Figure 1).

[2] Kitchin, in his recent work (2025), criticizes the metaphor of *data journeys* as overly simplistic, stating that it implies a linear and straightforward movement. He suggests that, in reality, data "replicate" rather than simply moving. I take a different position, aligning with Leonelli and Tempini (2020), who underline that data journeys are not linear or remotely smooth.

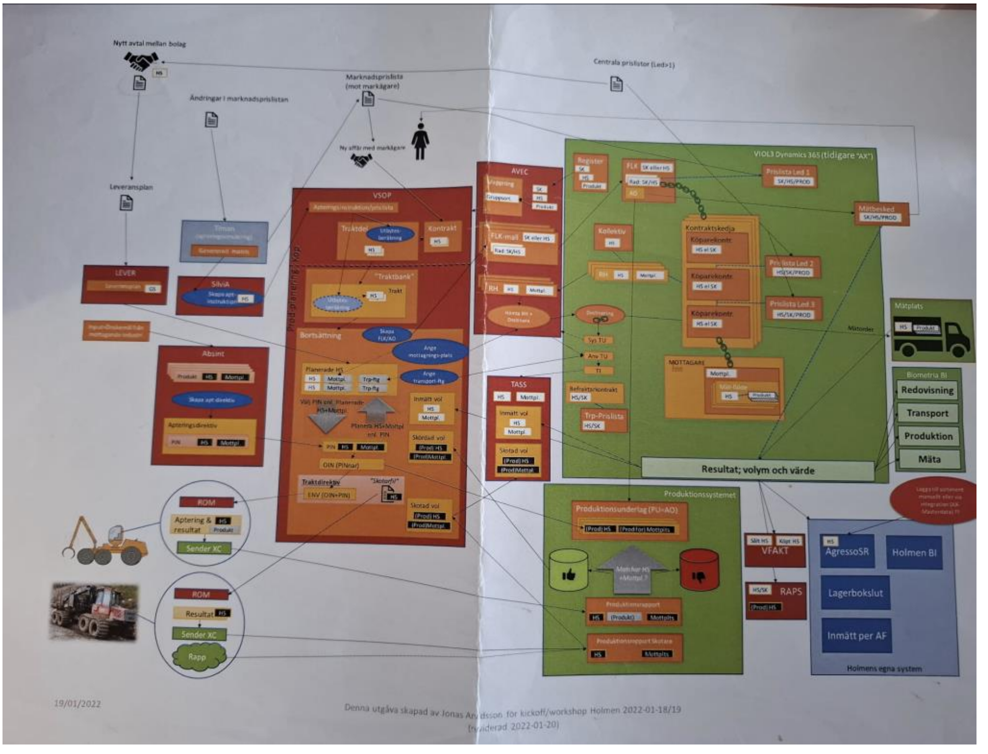

Figure 1. Overview of operational flow at Holmen, from contract initiation to timber production.

There are two research strands exploring the notion of data journeys (see Kitchin et al., 2025). The first research strand emphasizes the conceptual conditions that enable the motion of data, highlighting the significance of data practices, infrastructures, protocols, standards, and governance arrangements. These elements play a crucial role in facilitating flow and reuse of data, particularly in the context of knowledge production (Leonelli and Tempini, 2020; Beaulieu and Leonelli, 2022; Priego and Wareham, 2024). The other research strand reimagines data through a socio-material lens, highlighting that their creation and flow are intricately linked to the dynamics of data assemblages (see Kitchin, 2014a; Bates et al., 2016). Furthermore, it underlines how the material aspects and uncertainties of mediating technologies shape the politics and power of data (Bates et al., 2016). Despite their different emphases, both strands agree that data journeys are non-linear, situated, and shaped by socio-technical conditions – reflecting the view of data as not being selfcontained or inherently mobile. In my work, I draw from both strands of research on data journeys. The first stream, with its focus on data infrastructures, standards, and governance, helped me analyze the enabling conditions of circulation, linking directly to the use of data liquidity (e.g., the absence of data strategy in Paper 3, issues of connectivity in data infrastructure in Paper 4). The second strand, which highlights the situated and material dynamics of data movement, allowed me to capture the friction to which data were exposed to through reinterpretation, validation, and recombination.

3.1 Data Liquidity

To deepen this perspective, I turn to the concept of data liquidity, which complements the idea of data journeys by shifting the focus from *where* data move to *what enables* them to move. Originally a term from finance, liquidity refers to the ease with which assets can be exchanged without losing value (Piccoli et al., 2022). Specifically, in financial markets, asset liquidity explains how quickly and efficiently an asset can be bought or sold without its price being significantly affected (Le and Gregoriou, 2020; Fang et al., 2014). High liquidity in this context means that assets can be exchanged rapidly and at prices close to market value, whereas low liquidity signals difficulties in executing transactions without price impacts or additional costs (Myers and Rajan, 1998). This notion of liquidity is not limited to financial markets. Yuchtman and Seashore (1967), for instance, distinguish between different types of organizational resources, noting that some are relatively "liquid" in the traditional economic sense, making them readily exchangeable for other kinds of resources. In health informatics, liquidity has been articulated as a design principle, where it describes the ease with which clinical and patient data can flow across systems to support care, research, and innovation (e.g., Mandl and Kohane, 2009; Hripcsak and Albers, 2013).

In this light, applying the liquidity metaphor to data invites us to think beyond simple movement, toward how data are repurposed, reinterpreted, and integrated into new contexts. However, unlike financial assets, data rarely travel without transformation (Alaimo and Kallinikos, 2024). As they move, their meaning, interpretation, and relevance may shift (Leonelli and Tempini, 2020). From this perspective, it becomes possible to see a close connection between data journeys and data liquidity. Data journeys emphasize the routes, transformations, and frictions that data encounter across contexts (Leonelli and Tempini, 2020; Priego and Wareham, 2024), whereas data liquidity shifts attention to the conditions that enable such movement. It refers to the extent to which data can be accessed, reused, and recombined across systems and settings (Piccoli et al., 2022). Taken together, this suggests that data liquidity is what makes data journeys possible; data journeys are how data liquidity is realized in practice.

Although the concept of data liquidity remains underdeveloped in IS research, scholars have explored the enabling processes through which data become technically mobile, most notably through the notion of *liquefaction*. Liquefaction refers to both a capacity and a process. First, it describes the *capacity* of digital representations to be abstracted from their physical referents (Lusch and Nambisan, 2015; Alaimo and Kallinikos, 2024; Monteiro and Parmiggiani, 2019). Second, it outlines the *process* of abstraction, digitization, and standardization that makes data computationally manipulable and potentially recombinable across contexts and platforms (e.g., Lycett, 2013; Monteiro, 2022). This decoupling enables the digital forms to be recombined and mobilized across contexts. Monteiro and Parmiggiani (2019) describe liquefaction as the transformation of physical objects, processes, or qualities into digital representations that are not linked to their material referents. Alaimo and Kallinikos (2024) similarly argue that the very act of making data involves liquefying and reshaping the real. Still, the representational capacity of data is exactly that– capacity (Mikalsen and Monteiro, 2021, p. 1715). From this, we can deduce that liquefaction is a necessary, but not sufficient, condition for data liquidity. To make data meaningful or "liquid" (i.e., usable across systems and contexts), we need to do much more than just digitize reality, we need to embed the data in real, everyday practices (see also Mikalsen and Monteiro, 2021). Although liquefaction enables the potential for data to circulate, actual movement, recombination, and reuse depend on broader institutional, organizational, and data infrastructure arrangements (Bates, 2018). Data liquidity is what makes data journeys possible, but neither liquidity nor the data journeys it enables is automatic or frictionless.

3.2 Data Friction

In parallel with friction in physics, data friction occurs at the interface of two "surfaces" – two points where data move. Data rarely move without resistance (Edwards et al., 2011). As Borgman (2015) puts it, data do not "flow like oil" (p. 19), but are impeded and resisted. Edwards (2010) introduces the concept of *data friction* through a vivid metaphor:

> *Whereas computational friction expresses the struggle involved in transforming data into information and knowledge [...] data friction expresses a more primitive form of resistance – the costs in time, energy, and attention required simply to collect, check, store, move, receive, and access data. Whenever data travel – whether from one place on Earth to another, from one machine (or computer) to another, or from one medium (e.g. punch cards) to another (e.g. magnetic tape) – data friction impedes their movement" (Edwards, 2010, p. 84).*

Data friction can be understood from different angles and analyzed across different levels. First, Edwards (2010) directs attention to infrastructural frictions, the persistent resistances that accumulate in the technical management and movement of data. White (2017) extends this view by showing how such frictions appear as "breaks, stoppages, and disjunctures" (p. 93) within data journeys. This perspective views data friction as a practice that shapes how data are slowed down, delayed, or transformed in meaning. Aula's (2019) empirical work on health data governance in Finland exemplifies this dynamic. The author shows how institutional friction, legal ambiguities, misaligned policies, and competing ethical commitments constrain the reuse of health data, despite technical capacity. By contrast, Bonde et al. (2019) turn our attention to the everyday practices of repurposing healthcare data, showing how frictions emerge when clinicians negotiate formats, relevance, and meaning to make data useful in new settings.

Tsing's (2005) approach on *friction* provides another lens to the discussion. While she does not discuss data specifically, her ethnography offers a more relational and interpretive view. She describes friction as the generative force that emerges when difference meets movement: the "awkward, unequal, unstable, and creative qualities of interconnection across difference. It is not a synonym for resistance. Friction reminds us that heterogeneous and unequal encounters can lead to new arrangements of culture and power."(p, 4). This perspective highlights how friction can create obstacles but also opportunities for transformation.

Considering the above, I approach data friction as a condition that became visible in data infrastructures, in the institutional rules that frame their use, and in the everyday work of people working with data. Looking at data friction from these different perspectives was important because it allowed me to see both the constraints and the possibilities that shape data practices. Edwards (2010), for instance, helped me see *where* frictions arise and how they emerge in institutional and infrastructural forms. Further, Tsing's (2005) and Bates's (2018) work encouraged me to reflect on *how* these frictions can shape what counts as meaningful, and for whom.

3.3 Practice-Based View

This dissertation began with the question of how data are governed in practice. I turned to what is broadly referred to as practice theory, a field marked by conceptual plurality and increasing importance across the social sciences. Terms such as *practice idioms*, *praxeology*, *practice-based studies*, and *practice lens* reflect the diverse intellectual roots and evolving methodological applications of the field. Since the 1970s, scholars have used these concepts to examine domains as varied as strategy (e.g., Vaara and Whittington, 2012), change in work practices (e.g., Orlikowski and Scott, 2021), and knowledge (e.g., Orlikowski, 2002; Monteiro, 2022). Practice has been conceptualized in multiple ways across the literature. For example, it has been perceived as embodied action (Bourdieu, 1990), as structured through language, tools, and symbols (Turner, 1994), as a system of mediated activity (Engeström et al., 1999), and as a form of situated knowing-in-action (Nicolini, 2012; Knorr Cetina, 2001).

As a point of departure, I began by engaging closely with what domain experts in my investigated context did and said (Nicolini, 2017). However, understanding practices demanded more than surface-level observation.

Specifically, it required an inquiry into their conditions of possibility (Bourdieu and Wacquant, 1992). Practices are not merely activities, but also are meaning-making, identity-forming, and order-producing processes (Chia and Holt, 2008). This called for an examination of the historical, material, and social circumstances under which these practices emerged, the tensions they carried, and the outcomes they generated (Nicolini, 2017). As I moved deeper into intellectual traditions, from first-generation practice theorists like Bourdieu (1990) and Giddens (1984), who established the foundations for practice theory, to second-generation scholars such as Schatzki (2001), who expanded and reinterpreted it, I came to realize that "practice theory" is, in many ways, a misnomer (see Nicolini, 2017). There is no singular or unified theory of practice. As Schatzki (2001) notes, the term practice acts more as a signpost than as a formula. It points to a loosely defined but reconstructive social ontology, a way of understanding the social world through what people do, rather than through fixed structures or isolated actors.

Inspired by Nicolini (2012), I began to treat practice as an open-ended orientation, a methodological and conceptual approach to engaging with how social life is enacted in practice. This orientation allowed me to see data governance not as a set of predefined rules, roles, or frameworks (see Khatri and Brown, 2010; Abraham et al., 2019), but as a process that unfolds through everyday activities, through data work, decision-making, and negotiation. Thus, I draw from what Nicolini (2012) calls a "theory-method package" (p. 219) to align my ontological and methodological commitments. In doing so, I used practice theory both as a perspective (see Orlikowski, 2010) and as a toolkit for investigating the situated, emergent, and socio-technical nature of data work across my cases (Nicolini, 2012). Although this flexibility allowed me to engage with a variety of theoretical strands, I found that they share a common focus understanding how action shapes the social world (Feldman and Orlikowski, 2011). Different theorists emphasize different elements such as structure, agency, knowledge, or materiality, but generally subscribe to a shared set of analytical moves (Nicolini, 2012; 2017). This became foundational in how I came to conceptualize data governance in this dissertation. With this grounding, I will use the next section to describe the key tenets of the practice-based view and show how they appear across my research and contribute to rethinking data governance.

3.4 Practices in Context

In the preceding section (3.3), I elaborated on how I view my work through a practice-based approach. Now, I want to explain how practices are reflected more specifically in my work and papers. In my work, I approach *practice* as "*recurrent, materially bounded and situated action engaged in by members of a community*" (Orlikowski, 2002, p. 256). This definition encapsulates key commitments of the practice-based view, including the embeddedness of action in socio-technical contexts, emergence, iteration, and the performative nature of organizing. In this section, I outline how these principles of the practice-based perspective inform both the design of and the analyses in my systematic review and empirical studies. By doing so, I show how the practice-based view framed my understanding of data work and data governance.

One of the most critical aspects is that practices are never isolated or abstract; they are always embedded in specific social, historical, and material contexts that shape what is possible and meaningful (Nicolini, 2012; Nicolini and Monteiro, 2017). At the same time, technologies are not neutral but they are woven into everyday practice, shaped by and shaping the ways in which people work (Orlikowski, 2000). Nicolini (2012) similarly remind us that even small, individual acts draw on collective histories, institutional norms, and socio-material arrangements. This idea that people and tools continuously shape each other has been central to how I understand and analyze data governance. In Paper 2, data governance (although I did not frame it as such at that time) unfolds as actors adapt and negotiate shared digital platforms and practices shaped by collaboration and power asymmetries. Paper 1 provides a conceptual foundation, illustrating how managing AI involves socio-technical negotiation. This framing helps to show how data governance is unfolded in the empirical cases. Paper 3 explores the daily realities of forestry data work. It presents two challenges emerging from data work practices: the "exploration loop," where practitioners experiment with tools but fail to support the transformation of practices, and the "temporality paradox," where the nature of data analytics clashes with long-term forest management. Both practices reveal the "situatedness" of data governance. In other words, data practices must be continually adjusted to fit the social and environmental realities of work.

Paper 4 explores how data are not simply circulated across contexts, but interpreted, validated, and corrected through hands-on and field-based work for AI use.

Additionally, practices are dynamic by nature and emerge through repetition and constant evolving (Antonacopoulou, 2008). As Nicolini (2009) explains, practices are "stretched out" across time and space, making them inherently open to disruption, contradiction, and transformation. Because of their iterative character, practices rarely remain stable but they evolve as actors engage with changing tools, expectations, and organizational relationships. Such tensions show how misalignments, whether triggered by technological innovations, competing institutional logics, or organizational asymmetries, are not signs of failure but sources of adaptation and change (Antonacopoulou, 2008). Tensions enact transformations. In my research, such dynamics are present across three empirical materials. In Paper 2, tensions between collaboration and competition among actors within an innovation cluster reveal how this dynamic can be managed for digital transformation initiatives. In Paper 3, the data work practices reflect how forest professionals develop a digital mindset to navigate tensions between short-term data analytics and long-term sustainability goals and understand the challenges of exploration and exploitation.

3.5 Theoretical Synthesis: Bridging the Theoretical Approaches

As my research progressed, it turned into an evolving journey of understanding data governance as an emergent and situated phenomenon. Therefore, the theoretical approaches were shaped alongside the empirical insights. To make sense of the complexity encountered in the field, I drew on five perspectives at different stages of the research: the practice-based view (applied in all papers, especially Papers 3 and 4) (Feldman and Orlikowski, 2011; Orlikowski, 2002; Orlikowski and Scott, 2021; Aaltonen and Stelmaszak, 2024), the socio-technical approach (used throughout all papers) (Bostrom and Heinen, 1977; Mumford, 2000; Sarker et al., 2019), paradoxical tensions (used mainly in Papers 2 and 3) (Smith and Lewis, 2011), Normalization Process Theory (NPT) (used in Paper 3) (Carroll et al., 2023; Hogan-Murphy et al., 2021), and data journeys (used in Paper 4) (Leonelli and Tempini, 2020). These theoretical approaches were introduced as needed to interpret and support the findings. Their use, as well as their methodological implications, are discussed in detail within the individual papers. In this section, I focus instead on the theoretical synthesis that emerged over the course of the dissertation work. Thus, I articulate the core conceptual contributions that developed through empirical synthesis. These include the practice-based view, which underpins the entire thesis, and three additional concepts: data journeys, data liquidity (Piccoli et al., 2022), and data friction (Bates, 2018; Edwards, 2011), which emerged as part of the synthesis process.

As described before, the practice-based view provided an analytical orientation across the dissertation work. It directed attention to the situated, socio-technical, and collaborative nature of everyday work. The concept of *data journeys* emerged most explicitly in Paper 4 but proved useful beyond the individual paper. Specifically, in Paper 4, the notion of data journeys was used to explore how data are produced, interpreted, and shared across sites, revealing how these movements enable or constrain effective AI use. In the dissertation, data journeys have served as a broader analytical lens for tracing how data governance unfolds through the situated movement of data. In parallel, the concept of *data liquidity* emerged through the comparative analysis. Although data liquidity was not part of the initial theoretical framing, it became increasingly important in tracing how actors sought to make data mobile, trustworthy, and reusable in support of goals such as AI use (Paper 4) or digital transformation efforts (Papers 2 and 3). In Paper 3, efforts to normalize data analytics practices involved the reconfiguration of data infrastructures and practices to support broader circulation across timeframes. In Paper 4, data liquidity was foregrounded in the structuring of data work to enable reuse across systems, illustrating the design and labor required to support data movement.

Similarly, *data friction* provided a lens for understanding the interruptions and constraints that inhibited or redirected data flows. Like data liquidity, this concept emerged through synthesis, as recurring patterns of resistance became evident across the empirical material. In Paper 2, data friction was visible in misaligned institutional logics, fragile trust relations, power dynamics, and asymmetries, and a lack of shared standards. In Paper 3, it surfaced through the "temporality paradox," where data-driven experimentation clashed with long-term sustainability aims, and in the "exploration loop," where data lacked sufficient grounding to inform decision-making. In Paper 4, data friction materialized at infrastructural handover points, where mismatches between data formats and user expectations required interpretive work, negotiation, and workaround solutions.

Together, these lenses formed the conceptual foundation of the dissertation's theoretical contribution. The following table (Table 2) summarizes these theoretical approaches by outlining their core concepts, contributions to understanding data governance, applications across the dissertation, and how they were traced through specific cases.

Table 2. Overview of the theoretical approaches

Theoretical Approach	Core Idea	Contribution to Data Governance	Relevant Work	Application to Dissertation
Practice-based view	Practices are situated, collaborative, material, and emergent.	Reveals data governance as emerging through informal, context-specific data work practices.	Feldman and Orlikowski, 2011; Orlikowski, 2002; Orlikowski and Scott, 2021; Aaltonen and Stelmaszak, 2024; Parmiggiani et al., 2024	All papers (especially 3 and 4)
Data Journeys	Data move across contexts and sites, transform and gain new meaning.	Traces how data are mobilized, reshaped, and reinterpreted across systems.	Leonelli and Tempini, 2020; Leonelli, 2019; Bates et al.,	Paper 4 but also emerged in the synthesis

			2016; Bates, 2018	
Data Liquidity	Condition that allows data to flow (easily) and be reused.	Used to explain how barriers to data mobility hinder trust, reuse, and AI implementation, and how data governance practices are reconfigured to support liquidity across systems.	Piccoli et al., 2022; Lycett 2013	Emerged in the synthesis
Data Friction	Condition that constrains data mobility by introducing delays, breakdowns, or resistance across sites.	Outlines how data governance challenges emerge through interruptions, misalignments, and resistances in the flow and use of data across socio-technical systems.	Bates, 2018; Edwards et al. (2011); Edwards, 2010; Aula, 2019; Bonde et al. (2019)	Emerged in the synthesis

4. Research Design

This chapter synthesizes the methodological approach that underpinned the dissertation, drawing together insights and reflections developed over the course of my research. Methodological choices are discussed in detail in each of the three empirical papers, whereas this chapter takes a step back to reflect on the broader research design and the reasoning that guided it. It discusses how the interpretive stance, adoption of phenomenon-based theorizing (Section 4.1), and the use of grounded theory methodology (GTM) (Section 4.2) evolved during the course of my PhD journey.

4.1 Interpretive Foundations and Phenomenon-Based Theorization

My research approach was grounded in an interpretivist paradigm, which stands in contrast to the positivist tradition. Whereas positivism aims to uncover universal laws and objective truths in a manner similar to the natural sciences (Lee, 1999), interpretivism views the social world as constructed, dynamic, and open to multiple interpretations.

Ontologically, interpretivism is based on constructivist assumptions (Berger and Luckmann, 1967; Leonardi and Barley, 2008). As Orlikowski and Baroudi (1991) explain:

> *Ontologically, interpretive information systems research assumes that the social world (that is, social relationships, organizations, division of labours) are not 'given'. Rather, the world is produced and reinforced by humans through action and interaction.* (p. 14)

In this view, reality is not fixed or objective. On the contrary, it is fluid and subject to varying perceptions. This implies that cognitive elements such as meanings, beliefs, and intentions are central to understanding the world (Chowdhury, 2019). This focus is further emphasized in the interpretivist goal to understand actors' own views of their social world and their roles within it (Goldkuhl, 2012). My empirical work reflected this stance: rather than encountering a single, coherent reality, I observed a range of actors' interpretations, multiple levels of data understanding and literacy, and differing meanings that actors attached to the same processes and practices.

In interpretivism, ontology and epistemology are intertwined (Goldkuhl, 2012). From this perspective, interpretive research seeks understanding through interpretation. Researchers aim to uncover the "existing meaning systems shared by the actors" (Orlikowski and Baroudi, 1991, p. 15). My research is situated in this tradition, which understands knowledge as constructed through engagement with the world and with those experiencing it. As Chowdhury (2019, p. 104) puts it, interpretive researchers assume that:

> *there is more than meets the eye, and this can only be understood by engaging with participants and inquiring about how they construct their worldviews.* (p. 104)

This orientation led me to conceptualize data governance as an emergent phenomenon that unfolds through ongoing interactions between human actors and digital artifacts. Consequently, my methodology emphasized engagement and immersion in the field (Orlikowski and Baroudi, 1991; Walsham, 2006), seeking to understand how people make sense of their practices and how these practices evolve.

Aligned with this philosophical foundation, I employed Grounded Theory Methodology (GTM). GTM is paradigmatically neutral and has been successfully applied across positivist, interpretive, and critical paradigms (Urquhart et al., 2010; Orlikowski, 1993; Cecez-Kecmanovic et al., 2008). In my research, I applied GTM within an interpretive tradition, using it as a flexible, iterative, and abductive approach (Reichertz, 2007). The idea of abduction has gained increasing prominence in the recent GT discourse as a central mode of reasoning. For instance, Charmaz states the following:

> *Why is grounded theory an abductive method? Because grounded theory involves reasoning about experience for making theoretical conjectures – inferences – and then checking them through further experience – empirical data. In this sense,*

grounded theory methods are abductive…. In short, grounded theory relies on reasoning – making inferences – about empirical experience. Thus a major strength of the grounded theory method is that these budding conceptualizations can lead researchers in the most useful, emergent and often unanticipated theoretical direction to understand their data. (Charmaz, 2014, p. 201, cited in Flick, 2019).

This approach is reinforced by phenomenon-based theorizing, which shaped my broader research design. In practical terms, this meant allowing the empirical material to shape the theoretical focus, rather than fitting observations into predefined categories (Von Krogh et al., 2012; Fisher et al., 2021; Gregory and Henfridsson, 2021). In this study, I focus on how organizations engage with data governance; a topic that is timely, under-theorized, and unfolds in ways that challenge established assumptions (Alvesson and Sandberg, 2020). Hence, this approach made it possible to pay attention to moments of ambiguity, contradiction, and improvisation.

4.2 Ground Theory as Methodology and Experience

When I started investigating Holmen, I encountered all the challenges that a novice researcher faces when working with GTM for the first time. These are mainly related to how to apply the method and engage with the data. The richness of the empirical world I was entering made it challenging to decide how to shape the analytical process. Following Glaser (2002), I treated everything as data and adhered to the principle of "emergence," where concepts must earn their place in the analysis by demonstrating relevance (see Gregory and Henfridsson, 2021). What I gathered felt rich yet disconnected. I began to experience what Charmaz (2006) describes as:

seeing data everywhere and nowhere, gathering everything and nothing. The studied world seems so interesting (and probably is) that the ethnographer tries to master knowing it all. Mountains of unconnected data grow—they do not say much. What follows?

> *Low level description and, if a bit more sophisticated, lists of unintegrated categories.*

GTM was first introduced by Glaser and Strauss in *The Discovery of Grounded Theory* (1967). It was developed as a reaction against the functionalist paradigms that dominated sociology at the time. Since its initial use, it has become one of the most widely used qualitative research approaches in the social sciences (Wiesche et al., 2017; Birks et al., 2013). This has reached the point that, as Levina (2021) notes, "everybody does grounded theorizing, but not everybody knows that they are doing it." At its core, GT is "*engaging a phenomenon from the perspective of those living it*" (Corley, 2015, p. 601). Creswell (2013) explains that grounded theory is:

> *a qualitative research design in which the inquirer generates a general explanation (a theory) of a process, an action, or an interaction shaped by the views of a large number of participants*. (p. 83)

In the context of IS research, GTM has been particularly effective in producing context-sensitive, process-oriented understandings of complex socio-technical phenomena (Urquhart et al., 2010). However, its application is far from straightforward (Timonen et al., 2018). One of the questions that GT researchers face most often is: "Which version of grounded theory are you using?" This question reflects the method's ongoing evolution and the different traditions within the method. As Matavire and Brown (2013) note, the most visible divide is between "classic GT" and "evolved GT," a distinction that points to deeper philosophical and methodological differences.

In my initial readings of the seminal GT work books (Glaser, 1978; Glaser and Strauss, 1967; Corbin and Strauss, 2008), I thought I needed to choose between them two. Classic GTM, rooted in Barney Glaser's work, emphasizes the emergent nature of theory and advocates for minimal preconception. It promotes a process where the researcher allows categories to emerge through constant comparison (Glaser, 1978; Glaser and Strauss, 1967). In contrast, evolved GTM, shaped by Strauss and Corbin, introduces a more structured and interpretive process, acknowledging the researcher's active role in shaping analysis. This version includes detailed coding procedures, namely open, axial, and selective, and is informed by a more pragmatic stance (Corbin and Strauss, 2008; Strübing, 2019). The evolved GT has increasingly recognized the interpretive dimensions of research. In later editions, Corbin emphasizes researcher reflexivity and thus softens earlier technical rigidity (Corbin and Strauss, 2008). This interpretive turn is most explicit in Charmaz's constructivist grounded theory (CGT), which emphasizes that meaning and knowledge are co-constructed between researchers and participants (Charmaz, 2006). CGT views theory as an interpretation rather than a simple description of reality. Yet, as scholars like Corley (2015) argue "*GT has taken a life of its own*" (p. 602). Further, Birks et al. (2017) emphasize that researchers should move beyond the "schisms" between GT variants. Scholars suggest treating GT as a flexible set of principles rather than fixed packages that require choosing one over the others (Charmaz, 2006). In my work, I focused on the common ground across these traditions, trying to understand their philosophical foundations, and contexts (see Section 4.2). This perspective also shaped the way I approached my empirical work.

I approach the process iteratively, with each step informing the next through constant comparison (see Section 4.4 for further details on data sources and analysis). To see the story in my data, I relied on theoretical memos to make sense of the data and track the development of concepts and categories over time (Glaser, 1978; Charmaz, 2006; Birks et al., 2013; Lempert, 2007; Urquhart, 2013). In my memo writing, I worked to develop categories, contrasts, and questions that extended beyond the initial topic, following Lempert's (2007) guidance (Figure 2). Lastly, I used theoretical sampling to decide when and where to collect additional data, which allowed me to explore and refine the emerging themes (Birks et al., 2013).

Excerpt fron field notes (Holmen's Headquarters, 14th February, 2023)

After a one-hour meeting with wood buyers about data updates and volume estimations, I asked the respondent to summarize the session—its objectives and its results. The respondent explained that some data were missing from the Excel sheet. When asked which data were absent, and how this affected both work and planning, the conversation broadened into a discussion about the role of data in decision-making.The respondent described a common practice: when current data is uncertain or inconsistent, historical data is used as a reference point. This approach,referred to as both an "act" and a "pragmatic" solution, is not considered a failure but a practical way to keep operations moving. The respondent also confirmed the views of colleagues, noting that many rely on "good enough data".The respondent used the example of optimization program used for deliveries. The system can calculate the cheapest way to transport wood, suggesting for instance that 2,000 cubic meters should go by truck in January, by train in February, and by boat in March. On paper, this looks very exact. But the data fed into the program, such as yearly forecasts from buyers, is often just a guess. If those guesses are wrong, the entire optimized plan risks being wrong as well. The respondent described this as a good program but dependent on data that cannot always be trusted.The respondent explained that this way of working is tied closely to the challenges of digital transformation. Transformation, according to the respondent, is not only about buying new tools, but about changing how data are used ross the organization. With some frustration, the respondent pointed out that there are around twenty different systems in use, many of which do not communicate with each other. Because of this, data can look different depending on when and where they are accesses, sometimes recorded by measurement date, sometimes by delivery date. The same event may therefore appear differently in different systems, which creates a culture of caution around data. When I asked about tools, the respondent said that despite their availability most of the work still relies on "human knowledge" (repeated by the respondent several times) and past experience.Here the respondent pointed to the company's digital strategy roadmap as a way to move forward. The roadmap outlines five areas of focus: *digital planning, active leadership, best practice, communication, and follow-up*. In practice, this means developing better planning methods in the short term, while leaders actively coach and support change. It also means defining responsibilities for training and building clear routines (best practice), making sure expectations are communicated openly, and setting up follow-up systems that measure whether changes actually work. Over time, the plan stretches across three years: starting with pre-planning using current systems, then strengthening training and feedback, and eventually embedding more efficient digital routines into everyday work. For the respondent, this strategy connects directly to the everyday frustrations with data.

Questions for further comparison and coding:

- What counts as "good enough" in data, and who decides what is good enough, based on what criteria?
- How do users handle inconsistencies between systems?
- What data practices replace missing or unreliable system data?
- How does reliance on historical data shape current system use?

Figure 2. Memo taken during "shadowing," outlining the experiences and reflection of employees on data.

To place my work in the broader GT landscape, it is important to recognize the diverse kinds of outcomes this approach can generate. GTM does not always aim for grand theories. Instead, it can produce models, conceptual insights, or rich (thick) descriptions, each playing a different role in theory development (Wiesche et al., 2017). Thick descriptions, in particular, can provide deep, contextual insight into how phenomena unfold, for whom and why they matter (Wiesche et al., 2017). Similarly, in my research, thick descriptions became a way of theorizing (see Patton, 2014). Specifically, by tracing the situated and evolving dynamics of data governance, I was able to show the everyday tensions and negotiations around data, while also creating a foundation for further theorizing (see also Weick, 1995).

4.3 The Evolving Logic of Qualitative Case Study Design

As Yin (2018) explains, a case study "*investigates a contemporary phenomenon in depth within its real-world context, especially when the boundaries between phenomenon and context may not be clearly evident*" (p. 15). The case study approach fit my research well because it allowed me to stay sensitive to the context and follow how data governance played out in practice. More than a methodological choice, the case study became a flexible and evolving tool for theory development (Eisenhardt, 1989, 2021), one that adapted in response to shifting empirical realities and theoretical insights throughout the course of the project.

The research began during my master's studies at the Cluster of Forest Technology, where I set out to explore digital transformation initiatives in the forestry sector (Paper 2). This early study opened up the directions for the broader theoretical orientation of the dissertation. During my doctoral studies, I conducted two embedded case studies at Holmen (Yin, 2018). One examined the normalization of the digital mindset, and the data work practices that led to the evolution of this mindset. The study highlighted the emerging challenges arising from the nature of data and forest management and the lack of a data strategy (Paper 3). Paper 4 focused on data journeys as an important element of data work.

Across all three empirical studies, I examined multiple organizational levels as units of analysis, the roles and responsibilities of actors, and data infrastructures. This design enabled comparison across cases and supported the development of theoretical insights (Yin, 2018). It was guided by the interpretive tradition (Walsham, 1995, 2006; Klein and Myers, 1999) and focused on how organizational actors construct meaning around data, digital technology, and data governance. I also drew from the abductive logic of systematic combining (Dubois and Gadde, 2002), wherein theory and data interact through iterative processes. This meant that my early observations changed the initial research objectives and shifted the empirical focus and conceptual framing. This process resonates with what the authors call matching, a process of aligning theory and fieldwork through ongoing reflection and redesign.

To highlight and reflect on the limitations of the case study design, I acknowledge that case studies have been critiqued for their limited generalizability (Weick, 1969). However, later revisions of this view acknowledge their strength in theory-building (Weick, 1969). My aim with this work has been to provide statistical inference, but analytical generalization. This involves developing second-order theoretical constructs that clarify the observed settings and make it possible to anticipate patterns in comparable contexts (Yin, 2018; Lee and Baskerville, 2003).

4.4 Data Collection and Analysis

In examining the two organizations, the Cluster of Forest Technology and Holmen, I used similar data collection methods but adapted my data analysis to suit each context. This variation was due to differences in research objectives, data accessibility, and the duration of fieldwork in each setting. Papers 2 to 4 provide detailed descriptions of the specific data collection and analysis techniques used. The data I gathered are process data, defined by their rich and varied nature, as they capture how strategies, roles, and meanings developed over time and across organizational layers (Langley et al., 2013). As Langley (1999) and Pettigrew (1990) emphasize, such processes unfold not only over time but within broader organizational and contextual environments, and my data collection was intentionally designed to reflect that complexity. I used Atlas.ti for data management and applied the Gioia methodology to structure and visually organize the data (Gioia et al., 2013). Below, I discuss the rationale and process behind these methodological choices.

First, Paper 2, which investigates the tensions surrounding the digital transformation initiative in the Cluster of Forest Technology, initially took shape during my master's studies. In this work, my co-author and I collected data through a combination of semi-structured interviews, document analysis, and participant observation (Ritchie and Lewis, 2003; Mason, 2002). However, as I transitioned into my PhD work, both the paper's scope and the objectives evolved. I revisited the initial dataset with a more critical lens and complemented it with additional material, including observations from two events organized by the cluster. These events showcased ideas and solutions for improving operational efficiency and the value chain. For example, one demonstration presented the use of spatial data for mapping and planning forest activities. Another demonstration featured a forestry machine that integrates automation and digital control systems (Figure 3).

Figure 3. From the Forest Technology Cluster excursion on October 6, 2021, themed "The Digital Future of the Forest".

The expanded dataset allowed me to conduct a deeper analysis. Specifically, they helped me to trace developments over time and better understand how the cluster's digital initiatives were presented, discussed, and received in different settings. I coded the data using Braun's and Clarke's (2006) five-phase framework: familiarization with the data, initial coding, organizing codes into categories, developing sub-themes, and finalizing overarching themes.

A year after I started my PhD work, in April 2021, I began data collection at Holmen with semi-structured interviews (Table 3 for an overview). In approaching Holmen's case, I employed a GT design to allow theoretical insights to emerge directly from the data. This approach was well-suited to the exploratory nature of the study, especially as my primary objective was to investigate how AI and digital technologies have transformed established organizational practices. At this stage, I aimed to further explore the phenomena I had identified in my first study, while remaining open to new and emerging patterns. In this process, I was guided by what Charmaz (2006) describes as "*sensitizing concepts*," which in my case were *organizational practices* and *digital transformation*. These concepts served as interpretive tool and turned my focus on the key aspects of the data.

With this in mind, the first round of 13 semi-structured interviews (April 2021–October 2022) was exploratory as I was seeking to gain a deeper understanding of the forestry context in digital transformation. I employed intensive interviewing techniques as described by Charmaz (2006), which enabled the collection of rich, in-depth narratives of participants' experiences and perceptions.

Data Sources	Data Types
Primary data *Semi-structured interviews* (approximately 800 pages, transcribed verbatim)	-First wave (April 2021–October 2022): Thirteen semi-structured interviews with respondents including a CEO, a head of IT, forest planners, and business developers. -Second wave (November 2022–June 2023): Forty-two semi-structured interviews (5 supplementary from the previous wave), 30 to 90 minutes long, with respondents including data scientists, silviculture managers, forest planners, wood buyers, and forest managers. -Third wave (November 2023–October 2024): Two semi-structured interviews (100 min) with a natural value assessment specialist, and one interview with a project manager (62 min). Field notes: Notes were taken during field visits (96 hours) at Holmen offices in the northern (32 hours) and central (64 hours) regions, including “shadowing observations” (89 pages of detailed documentation). These included nine formal meetings with wood buyers, forest planners, data scientists, natural value assessment specialists, and business developers. Topics discussed included how predictive analytics can assist future sustainability goals, presentations and conversations about the Natural Value Inventory (NVI) project, informal conversations during lunch and coffee breaks with various employees (55 additional pages), and participation in a 3-hour event focused on sustainability and the future of the forestry industry with representatives of the Forest Industry Association (11 pages).

Secondary data *Archival data and visual images*	Public documentation: I reviewed and analyzed publicly available material including annual reports from 2002–2023 (1,573 pages). The company explicitly stated its sustainability goals for the first time in the year 2002 and established activities to reach them (although previous annual reports also referred to efforts to reduce environmental impacts). I reviewed *Skogsliv* [Forest Life], Holmen's magazine for private forest owners (Theme: Climate Adaptation, 2024, 48 pages). Internal data sources: I reviewed the company's internal blog, where an employee shared detailed accounts of their work practices and the systems used over the course of a working week (November 2019 to October 2024, 32 pages). In addition, I examined a range of internal documents and materials, including PowerPoint presentations on topics such as *The Future of Smart Forestry* (27 pages), *Ecological Landscape Planning* (10 pages), *The Vision for Forest Planning and Forest Data* (7 pages), and *Wrap-Up of the Sense Project* (14 pages). I also reviewed a short questionnaire related to the NVI initiatives, which was further elaborated through discussions with the natural value assessment specialist, providing contextual insights into how the initiative was understood and implemented. Lastly, I analyzed 4 videos (around 1.5 hour each) and around 70 images taken at Holmen's office. These were used to explain the company's data infrastructure – illustrating how data were stored, accessed, and integrated across systems and organizational practices.

Table 3. Overview of data sources.

This phase of context exploration focused on understanding the company's operations and established forestry practices. I became familiar with different types of forest management (strategic, tactical, and operational planning), forestry standards, the roles of the employees, and their work practices. In parallel, I began to understand how the company's business goals were intertwined with a strong commitment to sustainability and biodiversity. This realization emerged not just from documents (such as annual reports), but also from the language that people used to describe their daily work. One interview, in particular, stayed with me. A marketing assistant described their connection to the forest in terms that revealed a deeply rooted organizational ethos:

> *All of us who work here have a deep respect for the forest. It is something we engage with every day and something we all share in common. We respect that things take time and that one needs to be very conscious in the forestry industry. Therefore, we try to be careful and think things through. I believe this affects the way we make decisions, even when they are not directly connected to the forest.*

Asking questions about the use of different digital tools and projects that contribute to digital transformation and work change, I became familiar with the *Sense Project* (the purpose, evolution, and learning outcomes of which are detailed in Paper 3). The Sense Project was a "learning test" to frame and implement both AI and data-driven initiatives to create organizational value, exploring and reflecting on questions like:

> *How should we work...? How should we implement AI, and in what kind of context.? What data we should collect and use.? What methodologies should we use.?* (Project manager)

However, during the open coding phase of my data analysis (Charmaz, 2006; Gioia et al., 2013), it became evident that perceptions of what digital transformation is and how it affected organizational processes and work practices varied significantly across the organization. Although it was recognized *"*that the organization has been working with digital transformation for a long time in a light way*"* (Head of IT and Analytics), many employees (such as business developers, forest planners, and production managers) noted that their day-to-day practices had not changed significantly. Interestingly, those involved in the Sense Project articulated a strategic and future-oriented vision of digital transformation, but this perspective was not widely shared across the organization. When asked about their experiences and challenges and prompted to provide examples, employees frequently redirected the conversation to data-related challenges. What stood out was the consistency and emphasis of concerns such as "poor data quality," "data arrive too late," and, most notably, that "data are a guess." Two interviews were especially striking.

> *There is a lot of talk about digital transformation and what we can do with big data and AI. I think it is almost a buzzword to talk about these things. But we see a lot of interesting changes, and more data and applications are being used in our everyday work. So far, nothing has radically changed the planning process in the field. We have new data that can help us make better decisions, but still, we have to be out there. New technology has not replaced anything –it has only just improved some processes*. (Business developer)

The second interview centered on procurement planning and offered a different operational perspective. Despite the difference in context, both interviews shared a common thread: they highlighted how data, though increasingly present, had not yet become a transformative force in everyday decision-making. As the second interviewee put it:

> *It's very much guessing* [meaning the work practices] *and a limited control over the data. Yes, of course, we have numbers, for instance what we have in the area, what we bought in previous years, and where we should be by the end of the year. But until we reach this point, or even when we set broad purchase goals at the start of the year, we don't really know what's possible. Nor do we know exactly where to buy it. So yes, data are essentially guess*. (Delivery coordinator)

And the interviewee continued:

> *We don't have one system, we have like 20... And it is not easy for many reasons to trust the data and make the data flow*.

But how can data be a *guess*? And what are the "many reasons" that make it so difficult to trust and mobilize data in practice? Intrigued by this account, I asked to follow the second interviewee for non-participatory observation at Holmen's headquarters, to understand better how the interviewee worked and what the challenges of their work were. Employing the "shadowing technique" (Czarniawska, 2007), I accompanied the delivery coordinator for 32 hours, attending meetings, work routines, and spontaneous moments of decision-making. In the meantime, to understand the objectives of the fieldwork, I turned to the literature to better grasp the new phenomenon I was encountering, data governance (Gill et al., 2014). This decision aligns with the argument that GT research benefits from a continuous engagement with existing literature. Rather than avoiding prior work, a researcher can use literature to enhance their theoretical sensitivity and support abductive reasoning, helping them critically compare and refine emerging insights (Thornberg and Dunne, 2019).

I began asking how the organization managed data, what types of data were produced, through which systems, and how they were used across different functions. These questions soon expanded to include issues of ownership, access rights, and standards: Who owned the data? Who was responsible for their quality and accuracy? What standards guided how data were collected, shared, and maintained?

This shift in focus marked the beginning of a second, more targeted round of data collection of 42 semi-structured interviews (November 2022–June 2023). Guided by theoretical sampling principles, I selected participants (see Appendix 1 for an overview of respondents and their work with data) whose roles explicitly involved working with data, such as data scientists and participants who performed background data-related tasks such as forest planners (Urquhart, 2013). These actors played an important role in making data usable and reliable across the organization by ensuring that they could support daily operations and longer-term strategic decisions. Building on insights from the initial phase, I revised the interview protocols to probe more deeply into participants' challenges, experiences, and everyday involvement with data governance (Spradley, 1979). I asked them to describe how they accessed, cleaned, processed, and applied data in their roles while also reflecting on issues such as data ownership, quality standards, accountability, and data sharing. Additionally, through these discussions, I became increasingly familiar with Holmen's data infrastructure (its layers, limitations, and the ways in which it shaped how data circulated and were acted upon across the organization).

As my data collection, coding, and engagement with the literature progressed, I found myself wanting to gain deeper, more situated insights into how people actually worked with data. I decided to return to the field, this time shadowing a natural value assessment specialist over 96 hours.

This phase provided a clearer view into the practical realities of working with data. I followed the domain expert into the forest when conducting assessments and interpreting ecological features, asking them to narrate their reasoning aloud.

The expert showed me, in real time how the field app was used to enter, correct, and validate data on-site. Along the way, they pointed out how predefined system categories did not fully match what a user actually observed on the ground (Figure 4).

Figure 4. Performing natural value assessment and reporting data (May 19, 2023).

In the office and meeting rooms, the expert continued to walk me through the data work. For example, I attended a session where the expert and a group of data scientists revised a predictive model for natural value inventories. During these exchanges, the expert explained how different data sources were or were not integrated and how inconsistent standards across departments made data sharing challenging. Additionally, the expert demonstrated how datasets often had to be manually reformatted or interpreted before use. They openly discussed the compromises required when biological complexity met algorithmic logic. Some of the most valuable insights emerged in the so called the "in-between spaces": hallway chats, coffee breaks, and car rides. In these informal moments, the specialist reflected on the practical complexities of working with data, such as navigating competing goals, dealing with outdated systems, and reinterpreting data across contexts. These conversations offered a fuller picture of how data travelled: starting from production through processing and sense-making, and the obstacles that affected decision-making. As emphasized in the literature, such informal exchanges added vital "context" and "authenticity" and generated insights often missed in formal interviews (Patton, 2014; Swain and Spire, 2020). These everyday interactions were important to understanding how data became meaningful, actionable, and continuously interpreted in practice, and for whom.

Lastly, beyond observing these routines, I also engaged with secondary visual materials, such as photographs, videos, and PowerPoint presentations, as data in their own right (Figure 5).

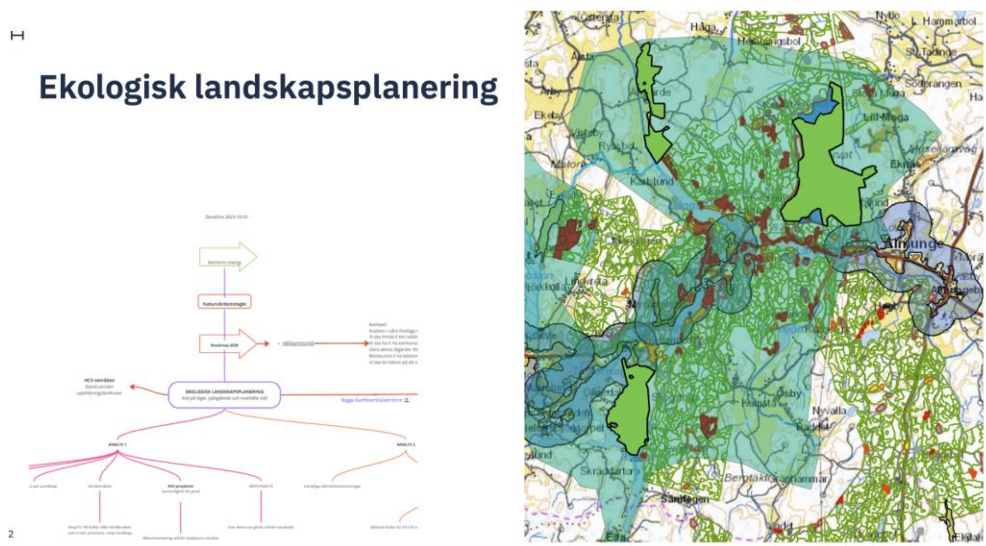

Figure 5. Slide from a presentation on April 4, 2023, linking strategic goals to mapped nature values, risk analysis, and proposed conservation zones.

These additional materials improved my understanding of the organizational context and supported methodological triangulation (Patton, 2014). For example, a presentation at Holmen explicitly connected biodiversity goals to predictive analytics projects, illustrating how sustainability was linked to digital transformation. This contrasted with employees' opinions, which often emphasized data frictions and uncertainty in daily practices. In this way, secondary data helped me trace how the organization formally framed its strategic priorities and legitimized particular narratives, while also providing contextual depth and a longitudinal perspective on how such narratives evolved (Patton, 2014).

Applying visual GT (Konecki, 2019), I used a "multi-slice imaging" approach to analyze these images across four layers: creation (who made each image and why), structure (how elements were visually organized), presentations (how and where they were displayed), and reception (how it was interpreted). This analytical framing enabled me to code visual and observational data alongside interview transcripts. This integration showed how visual representations mediated organizational narratives, reflected values embedded in data infrastructure, and contributed to the everyday enactment of data governance across both social and technical dimensions.

The third wave of interviews, conducted between November 2023 and October 2024, included two in-depth semi-structured interviews: one with a natural value assessment specialist and another with a project manager. These interviews aimed to validate the aggregated dimension and ensure theoretical depth (Birks et al., 2013; Urquhart et al., 2010). This final wave complemented ongoing observational work and helped confirm that the core themes were well-developed and consistently reflected across sources.

5. Ethical and Methodological Reflections

In this section, I reflect on my role as a researcher (Section 5.1) and the ethical and methodological considerations that shaped my study. These reflections cover the practical challenges of navigating the field, the relationships and trust that allowed open dialogue to happen, and the decisions I made in presenting the discussions. They also include how I approach and negotiate informed consent, how data were managed and protected (Section 5.2), and how broader questions of sustainability and data politics impacted my findings (Section 5.3). These factors influence my research process and what I was able to see, record, and share.

5.1 The Role of the Researcher

Looking back on my research journey, I realized that my role as an IS researcher was more complex than I initially thought. Data governance lies at the intersection of technological change, institutional rules, and societal challenges. I also found that the increasing attention paid to data and AI in society in recent years often opened doors, making it easier to approach projects and stakeholders. For instance, employees were eager to talk and explain the objectives and challenges of using predictive analytics (Paper 3). However, these conversations made me question whether such initiatives addressed the problems they set out to solve.

On the surface, these moments often carried a sense of momentum, a feeling that something meaningful was taking shape during the interviews. However, as I observed things more closely, I became aware of the ways in which stories about digital transformation and data were being shaped. I found myself paying attention not only to what was being said, but also to what was left unsaid. In those instances, my role shifted from simply following the course of events to questioning how the very idea of change was being defined and sustained in the organization. This questioning brought me back to my own stance as a researcher. Clarke (2009) captures this well by stressing that "*what can be known and how we can know are inseparable*" (p. 197). Mertens (2018) labels this axiology "the web of assumptions" that a researcher holds about the ethics of inquiry. For me, axiology was a constant presence in the field, urging me to consider how my choices, my tone, and even my body language influenced the discussions. Each decision, from framing an interview to choosing which threads to follow, became part of the research process itself.

In organizational research, retaining a critical distance from the subject matter is crucial in empirical studies, to enhance trustworthiness and facilitate access to data (Hayward and Cassel, 2018). Critical distance is a position that recognizes the importance of the work while allowing space to question and reframe it. As the authors note, the researcher and the researched can never be fully separate; rather, separation and closeness must be consciously managed. In this sense, researchers are not passive recorders but active participants in shaping the very realities that they study (ibid.). Weick (2002) similarly stresses the importance of keeping the researcher in focus, highlighting the need to attend to multiple dimensions of the research, including the responsibility to ensure that all voices are heard.

This view is also aligned with the principles of GMT, which rejects the myth of the researcher being a "blank slate" (Urquhart and Fernández, 2013; Charmaz, 2006). I carried my own experiences, background, and opinions into the field. The challenge was to acknowledge them without let them defining the phenomena I observed (Birks et al., 2013). Alvesson's and Sköldberg's (2018) notion of "reflective mode" research resonated here as any empirical material is already an interpretation, and my task was to remain attentive to the assumptions, language, and pre-understandings that guided my view. This requires a disciplined openness: remaining receptive to what unfolds while still using one's background to recognize meaningful patterns (Birks et al., 2013; Urquhart and Fernández, 2013).

I approached shadowing with the same mindset, recognizing that the researcher's role is adaptable. At times, I took the position of a direct observer, closely following organizational actors in their daily routines; at other times, I became an active participant in unfolding events. Shadowing is not a passive watching, but a performance-like relationship, where both my actions and those of the people I shadowed formed part of a dynamic, improvised process that revealed the organization's "front stage" and "back stage" (McDonald and Simpson, 2014). In my case, this meant walking alongside a natural value assessment specialist in the forest during site visits, listening to the respondents explaining the operational and ecological considerations behind their work, or sitting with production managers and forest planners at Holmen as they discussed issues of data quality and system integration. These moments often blurred the boundaries between observation and participation. In these moments, I was present as an outsider with the privilege of direct observation, but also as an insider to their unfolding narrative, asking questions and sometimes shifting the flow of the conversation (ibid.)

5.2 Ethical Considerations in Data Management and Informed Consent

As I mentioned in the previous section, some of my interactions with Holmen employees took place outside "formal" interviews, in everyday settings such as forest walks, lunch breaks, or coffee breaks between meetings. These informal conversations became an important part of the fieldwork, as they provided perspectives that added to (and in some cases validated) the findings from the structured interviews. During these discussions, employees shared reflections and experiences "off the record," that shaped my understanding of the organizational culture, dynamics, and structure.

One such moment that stayed with me occurred during a lunch conversation. When asked about the future of the industry, the employee replied, "*although things are changing, forestry is still very much a male-dominated environment, unfortunately.*" I found this response particularly interesting, since my question had been more focused on digital tools, and the future of Smart Forestry. This observation pointed to broader gender issues in the sector – issues of which I was already aware. For me, however, this observation served more as a sensitizing insight that allowed me to pay closer attention to how organizational structures and everyday interactions were affected by these issues. It also raised questions about how to ethically manage the data that emerged outside formal research settings. Swain and Spire (2020) have emphasized the need to distinguish between contextually embedded conversations, where participants knowingly engage with the researcher, and covert practices of "listening in" without consent.

I followed the principles of the EU's General Data Protection Regulation (GDPR) and thus I applied a data minimization strategy (Caeymaex et al., 2023). This means that I kept only data directly relevant to the study and excluded personal and sensitive details that might expose the identity of the respondents (ibid.). When I suspected that participants explicitly or implicitly shared a thought "off the record," I respected this by not including it in my dataset. I followed the suggestion of Klykken (2022), who stressed the importance of viewing informed consent as a continuous process. Therefore, I made sure to re-confirm consent whenever the context or the purpose changed. For example, before including screenshots or data from presentations, I informed the individuals about the purpose of their use. I also prefaced new interactions with a brief reminder of my role and the voluntary nature of participation in line with recommendations to renegotiate consent over time (Klykken, 2022).

5.3 Sustainability and Politics of Data

When I started my research, sustainability was not a focal concern. As the discussions with employees evolved, along with my understanding, this theme emerged in ways that balanced urgency with caution. Urgency came from the expectation that forestry should demonstrate visible contributions to climate goals. Caution arose from the recognition that forestry in Sweden is politically sensitive, entangled with broader questions of data ownership, welfare, biodiversity, and cultural heritage. In this setting, sustainability carried a variety of economic, cultural, and environmental concerns.

Hence, data emerged as a central language through which these concerns were expressed. Metrics for forest growth, biodiversity, and sustainability goals were used to support decision-making. What stood out for me in particular was the way in which such data were communicated in the industry. They were carefully framed to maintain trust among the member companies (in the case of the cluster) and the legitimacy of practices and decision-making (in the case of Holmen). This observation made me reflect on the politics of data, including how the decisions about what to measure, what to emphasize, and what to leave out, determined which aspects of sustainability were brought to the forefront and which were pushed into the background. Eventually, this raised further questions, such as to what extent sustainability could be captured through data, and what risks emerged when significant aspects remained unmeasured. In practice, discussions often moved beyond what data could express, touching on ecological complexities, the importance of cultural heritage, and social responsibilities (see also Holmen, *Future-Smart Forest*). Although these questions were not the central point of my study, they shaped my understanding of the forestry ecosystem. As such, in this landscape, data became a way of positioning forestry in relation to climate goals and legitimizing particular approaches to forest management. Some of these insights resonate with what I discuss in Paper 3 on the limitations of data analytics practices.

Understanding the politics of data required me, as a researcher, listened closely to how sustainability was discussed and made sense of data, and recognized the sensitivities that shaped what could be said and how. My role was not to remove the tensions that surfaced, but to observe, question, and reflect on the multiple ways in which forestry was represented through data. At times, this required me to hold back my own assumptions, allowing space for different perspectives to emerge, even when they were difficult to reconcile. Through these experiences, I learned that sustainability and data governance are deeply intertwined as the industry is moving from digital to green. Data were the medium through which forest responsibility, legitimacy, and possible futures were negotiated and expressed.

6. Research Context

The forestry sector offers a rich setting for studying data governance and data work because of the tensions it embodies. There are two main factors that make forestry unique: the nature of the industry itself and the nature of data. Forestry practices unfold on long timescales, often spanning a century or more, and decision-making relies heavily on historical data collected decades or even centuries ago (von Detten, 2011; Bettinger et al., 2016). Although such data may provide multiple insights, they frequently capture past climate conditions that no longer reflect the current forest reality or future scenarios (Yousefpour et al., 2012). This creates an important challenge, as efforts to meet sustainability goals require data that are both accurate and timely, to guide future predictions (Radke et al., 2017). The sector is also under pressure to respond to urgent environmental issues such as climate change and biodiversity loss (Ali, 2023).

Increasingly, forestry finds itself at the crossroads of two transformative pressures, the green transition and the digital transformation (Husain et al., 2022). On the one hand, society expects forests to be managed with biodiversity conservation and the preservation of cultural values in mind. On the other hand, rapid advances in digital technologies are reshaping how forest data are collected, analyzed, and applied in decision-making (Gabrys, 2020). Forestry plays a critical role in advancing sustainability by balancing ecological, economic, and social objectives (Ali, 2023). Forests are particularly significant as they sustain biodiversity and regulate the global carbon cycle, making them essential to climate change mitigation and human well-being (Gabrys, 2020; Hertog et al., 2022; Ali, 2023). Moreover, forestry is central to achieving the United Nations Sustainable Development Goals, particularly SDG 15, which calls for the protection, restoration, and sustainable management of forest ecosystems, including efforts to prevent desertification and minimize biodiversity loss (FAO, 2020, p. 13).

The longer I spent in this context, the more I noticed an interest in exploring digital technologies as a way to enhance productivity and meet sustainability goals. Yet beneath this ambition lay the less visible, messier realities of governing data in practice. In Papers 2, 3, and 4, I examined how digital technologies and data aggregation shaped and reconfigured forestry practices across my case sites. Here, I expand and engage in a broader dialogue on how the emergence of digital technologies and external socio-technical arrangements have contributed to the shaping and evolution of data governance. I begin by outlining how the forest is increasingly becoming a "site of data production," shaped by digital tools and regulatory demands for compliance and accountability (Section 6.1). I then present challenges that are less visible but still influence data governance in practice (Section 6.2).

6.1 The Evolution of the Swedish Forestry Sector as a "Site of Data Production"

Since the 18th century, Swedish forestry has undergone major transformations, from early manual labor and river log driving to the technologically advanced practices of today (Sandberg et al., 2014). During the 19th century, the introduction of steam-powered sawmills and more advanced harvesting machinery improved productivity (Albott et al., 2020). By the mid-20th century, timber production had increased, securing forestry's place as a pillar of Sweden's economy (Swedish Forestry Agency, 2015). In recent years, Sweden's forestry sector has also become a critical site of data production. Digital technologies are now used to monitor forest health and biodiversity in real time, aligning forestry practices with environmental sustainability goals (Zou et al., 2019).

Understanding how data work emerges in Swedish forestry requires an examination beyond the technological advancements. It involves tracing how the understanding of data and governing practices have shifted over time. This goes hand-in-hand with reflecting on and tracing broader transformations in forest policy, digital infrastructures, and institutional logics. These shift can be organized into three waves, each defined by changing assumptions about *what forest data are, how they gain legitimacy, and who acts on them and benefits from them*. In this section, I explore these shifts through three distinct but overlapping waves in Sweden's forest data evolution: (1) Centralized Control, (2) Reorienting Forest Data Toward Sustainability, and (3) Evolving Data Practices and Governance Complexity (Table 4).

Table 4. Waves of forestry data evolution.

Waves of forestry data evolution	**Approach to data**	**Digital technologies and types of data**	**Data liquidity**
Centralized Control	Instrumental and operational: Data supported timber extraction and planning. They were focused on measurable physical attributes for inventory and production.	Analog tools like diameter tapes, calipers, field notebooks, and aerial photography. Metrics focused on, e.g., wood volume and species dominance	Data were physically bounded and manually transferred.
Reorienting Forest Data Toward Sustainability	Accountability-oriented: Data expanded to track ecological conditions and social responsibilities, enabling certification and environmental compliance.	Remote sensing (satellites, LiDAR, drones), GIS, GPS, and forest certification systems. Datasets became more spatially explicit and ecologically rich.	Data became digitized but fragmented. Data silos remained a despite improved access and analytical tools.
Evolving Data Practices and Governance Complexity	Data are treated as strategic assets driving predictive, real-time, and adaptive forest governance. Emphasis on integration across systems and sustainability planning.	ML, Internet of Things (IoT)sensors, and high-resolution spatial modeling. Real-time tracking of carbon stocks, forest stress, and climate risks.	Data flows are technically possible but differ between institutions due to socio-technical arrangements.

First Wave: Centralized Control (since the 1920s)

The forestry sector has relied on empirical methods for improving forest management for over a century. Early forest surveys were based on visual estimation. In the 18th century, the emergence of mathematical tools established forest mensuration, which became more systematized by 1927. After the 1920s, progress in mathematical statistics and aerial photogrammetry further advanced forest surveying techniques (Zou et al., 2019).

However, there was still no unified international technical system for forest resource assessment at that time. A major turning point came with the 1923 launch of Sweden's National Forest Inventory (NFI). This marked the beginning of a new era in forest data governance. The main goal of the NFI was to quantify national forest assets and secure a sustainable timber supply. This goal was associated with the 1903 Forest Act, which emphasized reforestation and timber regulation (Breidenbach et al., 2021). Yet, during this period, forests were seen mainly as productive landscapes, valued for what they could provide, such as timber, pulp, and fuelwood (Lindahl et al., 2021; Gschwantner et al., 2022; Wang et al., 2025). This production-oriented model also defined how forestry work was practiced. Both labor and wood processing were highly physical and relied on manual tools. This resonates with what Zuboff (1988) vividly describes as "sensory experience" (p. 62).

Naturally, forest assessment prioritized what could be directly observed and measured. Foresters collected basic data on forest areas, wood stocks, dominant species, and forest age. Over time, more detailed measurements were added (Gschwantner et al., 2022). This data work was carried out almost entirely by state-employed professionals using analog tools like diameter tapes, calipers, and paper notebooks (Tomppo et al., 2010). The analog (data) infrastructure of the time significantly hindered data movement. There was minimal connectivity across forest agencies, and forest data were rarely reused or shared beyond their original purpose. Internally, data had to be physically transferred between forest planners and production leaders, often resulting in silos due to a lack of communication.

Later, the early experiments with Airborne Light Detection and Ranging (LiDAR) and Geographic Information Systems (GIS) began to emerge in the 1960s and 1970s. However, these advancements remained marginal, at least to begin with (Zou et al., 2019).

Second Wave: Reorienting Forest Data Toward Sustainability (since the 1980s)

From the 1980s, the identity and vision of the Swedish forestry began to shift in response to growing concerns over environmental degradation, biodiversity loss, and sustainability. Forests were no longer seen merely as timber resources but were gradually valued as complex ecosystems with ecological, cultural, and social significance (Löwgren and Segrell, 1991; Edwards, 2011; Holmen, Framtidssmart skog 2023; Wang et al., 2025). These changing expectations reshaped forest data practices as well. For example, forest inventories expanded to include indicators of ecological integrity, such as species composition, regeneration types, age structures, and deadwood. During this period, we see that the attention shifted to forest health assessment and ecological monitoring to achieve biodiversity goals (Kangas and Maltamo, 2006; Lindhal et al., 2017). In parallel, the introduction of forest certification schemes, such as the Forest Stewardship Council (FSC) in Sweden in 1993, created new demands for forest data systems. This is because the certification required data that demonstrated ecological conditions and social responsibilities, such as cultural heritage protection (Holmen, Framtidssmart skog, 2023; Lehtonen et al., 2021). In this way, forest inventories became a tool of accountability and were gradually used to ensure legal compliance, transparency, and environmental responsibility (Chirici et al., 2011; Kangas et al., 2018).

During this period, important technological developments occurred after the introduction of remote sensing technologies. We can classify their evolution in three periods: satellite imagery emerged during the 1980s, laser scanning was introduced in the 2000s, and photogrammetric point clouds became more common in the 2010s (Kangas et al., 2018). With each period, forest monitoring, management, and health assessment improved (Kangas et al., 2018; Miranda-Castro et al., 2022). In the beginning, the use of remote sensing was limited due to low-resolution images and small data volumes (Zou et al., 2019). Over time, however, improvements in data resolution and analytical methods made it more effective and allowed more accurate and large-scale forest management (ibid.).

As remote sensing technologies improved forest operations, the notion of *precision forestry* began to emerge. Derived from precision agriculture, precision forestry is defined as the use of computer devices, digital mapping, and spatial analysis to improve forest management through high-resolution data and decision support systems (Choudhry and O'Kelly, 2018; Figorilli et al., 2024). Meanwhile, by the mid-1990s, LiDAR emerged as a transformative technology in Swedish forestry, enabling detailed three-dimensional mapping of forest structure (Akay et al., 2009; Dassot et al., 2011; Nelson, 2013). The use of the LiDAR technology supported forest management tasks such as biomass estimation and damage detection. Over time, forest surveys relied more on a combination of remote sensing, GIS, and forest sampling within increasingly connected digital systems (Zou et al., 2019). For example, GIS provided a platform for organizing spatial and ecological data, whereas the Global Positioning System (GPS) enabled accurate mapping of boundaries. This supported forest management by making easier the movement of data across infrastructures and institutions (ibid.).

It is important to note that this growing reliance on data infrastructure also created several dependencies. For example, remote sensing tools have to be combined with field data and data infrastructure, which introduced new challenges. Integrating remote sensing into forest planning depended on organizational readiness, which varied widely (Akay et al., 2009). Yet even with increasing availability of datasets, the use of remote sensing data was hindered by fragmented data systems. Additionally, in many cases, skepticism about data accuracy persists, even when the data clearly outperformed traditional sources. In practice, the use of remote sensing was shaped by institutional structures, user trust, and the broader context in which these tools are applied (Fassnacht et al., 2024).

From the early 2000s, AI began transforming how forest knowledge was produced. Instead of relying on manual interpretation of satellite imagery, ML algorithms provided the possibility to automate the detection of forest changes, classify land use types, and model ecosystem functions

(Holzinger et al., 2014). This shift toward automation reconfigured data work practices once again. Data work became less manual and required skills in coding, data science, and remote analysis. As a result, forest governance became increasingly reliant on a variety of expertise and on professionals who could navigate both ecological complexity and digital systems. At the same time, as monitoring systems were used more broader, the importance of accurate, traceable and reliable data to support decision-making became clear (Kangas, 2016).

Third Wave: Evolving Data Practices and Governance Complexity (from 2010)

The third wave of forestry evolution signals a significant shift in how forests and forest data are managed, understood, and governed. Following the trajectory of other primary sectors such as agriculture, forestry is now beginning to move beyond treating data as a strategic resource for decision-making (Choudhry and O'Kelly, 2018; Gabrys, 2020). The integration of data-driven technologies into forestry practices introduces new ways of understanding and structuring forest governance. The "three-people-forest" mindset, described by Gabrys (2020), offers a critical perspective on this evolution. In particular, it highlights three distinct roles: those who manage forests, those who are governed by forest data, and those whose knowledge is embedded in – or left out of – algorithmic systems (ibid.).

With forests under pressure from climate change and socioeconomic demands, forest professionals are turning to digital technologies to both monitor and intervene in complex ecological systems (Choudhry and O'Kelly, 2018; Zou et al., 2019). As a result, the roles and responsibilities of forest managers are changing as well. Increasingly, AI is playing an important role in transforming traditional forestry operations. The use of ML algorithms and remote sensing allow for evaluation of alternative management strategies before they are implemented on the ground. We see more examples of ML algorithms being used in forest monitoring to classify tree species and detect disease outbreaks (Holzinger et al., 2024; Wang et al., 2025). Real-time data, for instance from Internet of Things (IoT) sensors in drones, enable continuous assessment of forest health and biodiversity indicators. Additionally, in forest management planning, AI supports predictive modeling of forest growth and risk assessment, including wildfire likelihood and pest dynamics (Holzinger et al., 2024).

However, despite data proliferation, the use of AI across the forestry sector is hindered by a series of challenges (Holmström, 2020). One of the key issues is the variation of digital maturity across forestry organizations. Despite growing interest in the potential of AI tools, many organizations still rely on legacy data systems and on manual data collection. A major challenge is the lack of in-house expertise in AI and data analytics, which reduces confidence and limits the ability for interpreting AI systems outputs (ibid.). Another, equally important, barrier is the reluctance to share data as stakeholders across the forestry value chain, such as private forest owners, industry actors, and authorities, often operate in data silos (ibid.).

In this section, I have presented the waves of forestry data practices to demonstrate how the sector has engaged with data and data governance over time. Circling back to the data governance waves elaborated in the theoretical background (Section 2.1), we can extrapolate that forestry has largely moved along the same trajectory as many other industries, albeit more slowly. What we are witnessing is a gradual transition in the mindset around data, from analog to digital and from administrative tools to strategic resources. I have highlighted how this shift in mindset has affected organizational roles related to data work and revealed the tensions affecting data movement.

6.2 The "Unseen": Insights and Reflections from the Holmen Case Study

Since the beginning, I was impressed by how much of Holmen's history seemed to mirror the story of Swedish forestry itself. The company traces its origins back to a paper mill established in 1609. By the late nineteenth century, it had become Mo och Domsjö AB, known as Modo. In 2000, the company changed its name to Holmen AB, reflecting a conscious shift away from the heavy industry to sustainability, renewable energy, and wood-based products. Today, Holmen manages over 1.3 million hectares of forest, with operations in forestry, paperboard, sawmills, and renewable energy, making it one of the country's largest private forest owners. Its operations include long-term forest planning, harvesting, silviculture, and timber logistics. Holmen supplies raw material to the group's sawmills and paper mills, while also playing a central role in forest management and climate adaptation. Over the decades, and alongside the broader transformation in the forestry sector (Section 6.1), Holmen has continually attempted to redefine how it works and understands its role within the industry. Paper 3 traces this process towards a more digitally oriented mindset, highlighting the tension between the forest's slowness and the accelerating pace of digital systems driven by real-time data and prediction. Paper 4 examines the everyday complexities of data work and how data governance is shaped. Here, I want to move beyond the analyses presented in the papers and depict the broader dynamics, the tensions, the culture, and the assumptions that affect how data are perceived, used, and moved within the organization, and demonstrate why data governance emerged as a theme.

Holmen takes pride in working with the forest, and this is reflected in the way decisions are made. Choices are weighed carefully, because a wrong move could harm the forest. In conversations, I came to see that this caution had a double impact. On the one hand, it reflected responsibility and care. On the other hand, it made it harder to move beyond established practices. The caution that protects the forest is also what slowed new ways of working. Many described how the same caution, at times, held back digital transformation initiatives. There was also recognition of the need to rethink this orientation. As the Head of IT and Analytics explained:

> *We practice seeing failure not as failure, but as a kind of success—because you always learn from it. Developing this continuous learning mindset is something we must practice.*

In 2015, as discussions around big data gained attention, Holmen, too, began to recognize the need to move toward digital transformation. By 2020, the company launched the Sense Project (see Paper 3), framing it as a digital transformation initiative, to respond to broader industry shifts, and an opportunity to explore the potential of data and AI. Looking back, I can see that the project generated enthusiasm and produced valuable learning outcomes.

Pilot projects showed, for instance, that integrating forest inventory data more systematically could improve harvest planning and support more informed operational decisions. Such cases demonstrated that Holmen already possessed valuable data assets. At the same time, experiments with automation and AI quickly revealed the limits of the existing data infrastructure. Efforts to work with higher-resolution datasets highlighted that the company lacked the technical environments needed to experiment safely. As participants noted, production systems demanded stability and predictability, leaving little room for the trial-and-error learning required to test new models. What was missing, in their view, was a kind of "lab space" (translated from Swedish) where data could be explored and combined without fear of disrupting daily operations (from a PowerPoint presentation for the Sense wrap-up). Despite the efforts taken, the project never led to digital transformation of processes or practices. On the contrary, it became an example of being "lost in transformation," between theory and practice, between ambition and implementation. Around forty employees participated over the course of two years, but many others remained unaware of the project's outcomes or uncertain about how these outcomes could be implemented. This ambiguity was also recognized internally. As one business developer said:

> *I think some people in Holmen Skog should say that we have been working with digital transformation for a long time in a light way, but we have some steps to take before we can say that we have transformed.*

This is also reflected in the fact that employees often described digital transformation as a matter of removing data friction. For example, a business developer explained digital transformation as the ability to:

> *gather the data from the source and collect it easily. Data should move as it's supposed to, without us having to check or manually transfer it. The overall idea is that we want our data to be handled as smoothly as possible.*

This revealed a deeper set of tensions. The challenge was not simply that digital (transformation) initiatives were hard to scale. Even deeper than this, the organization was struggling to shape a common understanding of data and a data culture. As highlighted in Papers 3 and 4, employees often operated with contradictory assumptions about what data meant. For some, the prospect of applying data in AI models was exciting, particularly when framed as a way to improve operational efficiency and decision-making. For many others, data and AI were perceived as little more than buzzwords that rarely translated into tangible changes in the organization or the established forest practices. Reflecting further, I came to see that although resistance to new technologies is common across many industries, it took on a particular character at Holmen. Here, developing a data culture often seemed to run against the core of the organization's history and identity. This does not mean that the company had not innovated before, but rather that legitimacy and trust were anchored in the physical forest. Employees repeatedly emphasized that the "physical comes first," and this emphasis became their (data) culture. The CEO's reflections captured this tension well:

> *I think it's more a tension between 'Do I believe in the new technology?' that's one thing, and the other, 'my experience, is that not worth anything more any longer?' Because in the end, someone needs to take a decision and he or she needs to feel that it's based on the best available information. To dare to trust data and new models is actually quite a large step.*

The more I explored this, the more issues of data quality and trust emerged, along with the circular question of what comes first: good data or trust in data? On the one hand, data quality was a constant issue that the forestry sector had faced for years. As one forest planner explained, they had learned to "work with good enough data in this industry." On the other hand, some respondents insisted that trust would only come when data were repeatedly validated:

> *we should trust the data when they have been validated multiple times. They need to be reliable. How good should the data be before we trust them?* (Marketing assistant)

At the same time, doubts about quality and trust were closely tied to another recurring theme: the movement of data. Even when reliable datasets existed, they often sat in silos, held by a particular department or system, and were difficult to integrate. In practice, this meant that data could be accurate but still unusable, arriving too late or requiring so much manual work that their value was diminished. These insights led me to shift my attention from the broad ambition of digital transformation to the everyday issues surrounding data per se.

7. Paper Summaries and Author's Involvement

In this chapter, I summarize the four appended papers. Table 5 provides an overview of the empirical data underpinning each study, the analytical approaches and theoretical frameworks employed, as well as my contributions to the respective author teams. The first two papers have been published in international journals; Paper 3 is currently under review and Paper 4 is in manuscript form. Whereas Papers 2, 3, and 4 present empirical investigations, Paper 1 is a systematic literature review.

Table 5. Summary of appended papers.

Paper	**Material**	**Analytical Approach**	**Author's Involvement**
1	Literature review on AI management covering 109 sources	Systematic literature review	First Author Literature research, data analysis, conceptualization*, writing*, editing*
2	Qualitative interviews (n=9), archival data, non-participatory observations	Qualitative case study	First Author Literature search*, data collection*, data analysis*, conceptualization*, writing*, editing*
3	Qualitative interviews (n=58), non-participatory observations, archival data	Qualitative case study	First Author Literature search, data collection, data analysis, conceptualization*, writing*, editing*, theoretical framing*

Paper	Material	Analytical Approach	Author's Involvement
4	Qualitative interviews (n=58), non-participatory observations, archival data	Qualitative case study	First Author Literature search, data collection, data analysis, conceptualization*, writing*, editing*, theoretical framing

*Multiple authors were involved in these activities.

As outlined in the introduction, this thesis adopts a phenomenon-driven approach, grounded in the empirical and conceptual complexity of data governance. This understanding has informed both the empirical materials and the theoretical contributions of the thesis. Across the four papers, I have explored how data governance is enacted and reshaped within socio-technical systems, with particular attention to forestry and data work practices, institutional conditions, and technological changes. Paper 1 provides a conceptual basis through a systematic literature review on AI management. The review aimed to map the emerging research landscape and identifying conceptual gaps relevant to AI management and data governance. As such, it served as a foundation for understanding the broader "territory" in which data governance is situated.

Papers 2, 3, and 4 further elaborate on the dynamics of data governance in practice. Paper 2 shows that paradoxical tensions, particularly between collaboration, competition, and knowledge sharing, deeply influence how digital transformation is organized and experienced. These tensions act as structuring forces that shape how digital initiatives and data-sharing practices are governed. In other words, the way that stakeholders negotiated trust, control, and openness shaped how data governance unfolded, especially in relation to intellectual property and shared digital platforms. Paper 3 explores the temporal and strategic tensions in efforts to implement data analytics into established routines and drive digital transformation. Specifically, it highlights how short-term data cycles often conflict with long-term sustainability goals, leading to data governance issues around data quality, data management, and data strategy. Paper 4 examines how data governance emerges through the situated data work of forestry professionals.

Each paper took its own path, shaped by empirical findings, theoretical development, and a constant dialogue with co-authors and reviewers. I invite the reader to view this thesis as a living and emergent whole, developed over the course of five years. Together, the papers contribute theoretically and empirically to understanding how data governance is enacted and negotiated in a world increasingly defined by data.

7.1 Extended Abstract for Paper 1

Koukouvinou, P. & Holmström, J. (2024). AI management beyond myth and hype: A systematic review and synthesis of the literature. *Pacific Asia Journal of the Association for Information Systems*, *16*(2). https://doi.org/10.17705/1pais.16201.

In this paper, we bridged and unpacked the literature on AI management. Our starting point was the observation that, although AI is increasingly central to the strategic agendas of firms, a holistic and integrated view of what AI management entails is still lacking. The literature is fragmented, reflecting disciplinary silos and a lack of cumulative tradition. This points to an underlying immaturity in current AI management research.

A major issue that we identified was the polarized discourse surrounding AI that often oscillates between two extremes: a dystopian fear of AI as a deterministic force and an overly optimistic vision of AI as a silver bullet. Scholars have noted the need to move beyond both naïve anxiety and exaggerated admiration for AI technologies. Moreover, we identified that much of the literature either focuses narrowly on the technical aspects of AI, downplaying its human and organizational dimensions, or emphasizes the social and managerial side, neglecting the technological characteristics of AI itself.

To address these gaps, we formulated the following research question: *What is the current state of AI management literature?* Through a systematic literature review of 109 sources published between 2010 and 2022, we mapped the fragmented landscape of AI management research and synthesized its dominant discussions. We identified four key thematic dimensions – *the data dimension, the labor dimension, the critical dimension*, and *the value dimension* – which we visualized in an integrated framework (Figure 6). This framework offers both scholars and practitioners a comprehensive overview of the field and its underlying assumptions, tensions, and research opportunities.

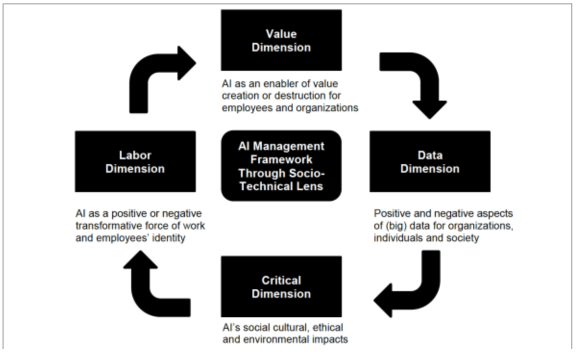

Figure 6. Dimensions of AI management literature identified using a socio-technical approach.

Furthermore, the review identifies several underexplored areas in the AI management literature, such as algorithmic governance, ethical tensions in AI deployment, human-AI collaboration, and the environmental costs of AI systems. By highlighting these gaps, we provided a clear agenda for future research and pointed out the importance of addressing both technological innovation and social responsibility.

7.2 Extended Abstract for Paper 2

Koukouvinou, P., Simbi, N. & Holmström, J. (2022). Managing unbounded digital transformation: exploring the role of tensions in a digital transformation initiative in the forestry industry. *Information Technology & People, 36*(8), 43–68. https://doi.org/10.1108/ITP-03-2020-0106.

This study presented an exploratory case study of the Cluster of Forest Technology, a collaborative innovation initiative in the Swedish forestry sector. The paper focused on the experiences of firms and actors within this regional cluster as they attempted to integrate digital technologies into traditional forestry practices. Drawing on interviews, internal documents, and field observations, the study explored how tensions, particularly between collaboration and competition, and between knowledge sharing and protection, shaped the digital transformation initiatives.

We identified five interrelated themes that affect the trajectory of digital transformation: leadership, knowledge flow, collaboration and competition, network creation, and asymmetric power. First, leadership was described as a key challenge since the ability to manage differing expectations and limited resources was essential to facilitate digital transformation initiative. Knowledge flow was highly valued but often remained limited due to the direct competition among the cluster members. The themes of collaboration and competition coexisted as the cluster members collaborated to share knowledge and tests ideas. Additionally, network creation was described as important in facilitating valuable connections to support innovation within the industry. Lastly, asymmetric power among dominant actors and smaller firms further complicated data sharing and undermined mutual trust.

These tensions were rooted in the unbounded nature of digital technologies, which allowed for reconfiguration and recombination across contexts, making traditional structures less stable and predictable. This fluidity enabled innovation, but also generated uncertainty, strategic ambiguity, and conflicts over control. To better understand how these tensions influenced transformation, the study adopted a paradox lens, emphasizing the need to manage tensions rather than eliminate them. This involved embracing competing demands as realities and developing adaptive approaches that supported innovation amid uncertainty.

By foregrounding these dynamics, the paper contributed to a deeper understanding of how digital transformation was enacted in practice. The findings revealed that tensions, especially between *collaboration, competition,* and *knowledge flow*, were central to how innovation unfolded and must be intentionally addressed (Figure 7).

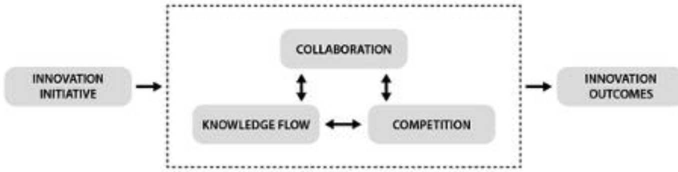

Figure 7. Paradoxical tensions in digital transformation initiatives.

Leadership and network creation were shown to be key enablers that helped organizations navigate conflicting demands, distribute knowledge, and sustain engagement. Balancing organizing and performing tensions was also crucial to coordinating efforts among diverse stakeholders.

This study provided insights for both researchers and practitioners. It highlighted that digital technologies can enable or constrain digital transformation initiatives. Therefore, managing digital transformation, especially in collaborative environments, required attention to the social, organizational, and relational dimensions that shape how technologies are integrated and used.

7.3 Extended Abstract for Paper 3

Koukouvinou, P., Carroll, N. & Holmström, J. (2025). Lost in transformation: Navigating the challenges of data-driven sustainability when you can't see the forest for the trees (Under review in an international journal).

This study illustrated a case where digital transformation fell short, yet the normalization of a digital mindset emerged as a learning outcome. Drawing on a 43-month qualitative case study of Holmen, we examined the challenges that organizations face when attempting to align data analytics with long-term sustainability goals. Our analysis focused on how data analytics practices and the inherently ambiguous nature of data shaped the direction and limits of sustainability transformation. Two core challenges became evident in the findings: the *temporality paradox,* where the short-term logic of predictive analytics clashes with the long time horizons of forest management and sustainability, and the *exploration loop*, where exploration without a strategy for hinders digital transformation. Prior Green IS research highlights how data analytics can improve sustainability through better reporting and data quality. Yet this study shifts the focus to a less explored issue of how data can (and cannot) represent reality, and the organizational complexities involved in producing and using it. To address this gap, we set out to challenge two prevailing assumptions. First, that data analytics is a reliable and inherently effective tool for decision-making, and, second, that digital transformation naturally follows the introduction of digital technologies. To explore these assumptions, we used NPT as a sensitizing lens for understanding the data and examined two long-term exploratory initiatives: the Sense Project and the predictive analysis project for the NVI. Both projects aimed to investigate how AI and data analytics could enhance forest management practices and support sustainability goals.

Our findings showed the importance of a digital mindset as a collective orientation toward understanding the capabilities and limitations of data and analytics, and the ability to adapt data practices over time. This mindset developed through three key practices: (1) removing technology-mediated constraints, (2) exploring data for green and digital transitions, and (3) assessing the use of data analytics. We identify that these practices unfolded across three phases: *coherence, cognitive participation,* and *collective action, leading to reflexive monitoring*.

The study made three core contributions to Green IS and data work literature. First, it contributed to the data work and analytics literature by showing how the ambiguity of data and the lack of a data strategy can impede sustainability efforts. Second, it advanced Green IS literature by stressing the importance of a digital mindset for facilitating sustainability transformation. In parallel, this shifts the focus away from narrow concerns with data quality. Third, it extended the application of NPT to sustainability-driven contexts, offering a process-based view of how data analytics practices are – or fail to be – embedded within data work practices.

7.4 Extended Abstract for Paper 4

Koukouvinou, P., Holmström, J. & Henfridsson, O. (2025). AI at work: Mapping data journeys for AI use in the forestry industry. (Manuscript).

As AI is increasingly being adopted across industries, data have become a critical organizational resource. Although AI depends on vast datasets, the reality of producing, moving, and governing data within organizations remains poorly understood. In particular, dominant data governance frameworks tend to assume that data are objective, complete, and readily available. This paper challenged that view by approaching data governance from a practice-based, socio-technical view and stresses that data governance is enacted in everyday work. We introduced the concept of *data journeys*, namely the movement and transformation of data across organizational sites, practices, and infrastructures, as an analytical tool to trace how data become usable for AI systems. Our empirical focus was a 43-month qualitative case study of Holmen Forest, a leading Swedish forestry company embarking on a digital transformation journey with the aim to improve practices through AI use.

Drawing from 58 semi-structured interviews, non-participatory observations, and archival material, our data revealed three key data work practices shaping AI use: *situated data construction, selective data sharing,* and *strategic data shielding*. These practices unfolded across socio-technical "sites," locations where the production, validation, and interpretation data happen. We empirically demonstrated that data work is what makes both data governance and data journeys possible. It is through the work of analyzing, interpreting, and filtering data that organizations govern their quality, accessibility, and value in context.

We showed that data governance is not fixed but a continually negotiated process. By doing so, we contributed to the data governance literature in three main ways. First, we reconceptualized data governance as an emergent, practice-based process embedded in data journeys. In doing so, we emphasized that it diverges from previous traditions rooted in IT governance and data quality management. Second, we introduced data journeys as both a conceptual and methodological tool for understanding and observing how data practices can enable or constrain AI use. Third, we provided practical insights by showing that data practices often seen as obstacles, such as strategic data shielding, can eventually serve to preserve trust and contextual integrity.

7.5 Additional Publications

The papers included in this thesis represent a journey of research and reflection that has unfolded over several years. Along the way, I have published parts of this work in other forms and outlets. Looking back, I can see that these earlier publications were stepping stones that helped me clarify my thinking and gradually build toward the ideas that I now bring together in the appended papers. Other relevant publications include:

- Koukouvinou, P. & Holmström, J. (2022). AI management beyond the narratives of dystopian nightmares and utopian dreams: A systematic review and synthesis of the literature. In *European Conference on Information Systems (ECIS), Timisoara, Romania, 18-24 June, 2022*.

- Koukouvinou, P., Ademaj, G., Sarker, S. & Holmström, J. (2023). Ghost in the Machine: Theorizing data knowledge in the Age of Intelligent Technologies. In *International Conference on Information Systems (ICIS) 2023, Hyderabad, India, December 10-13, 2023*. (Vol. 22). AIS eLibrary.

- Sundberg, L., Kostis, A., Koukouvinou, P., Holmström, J. & Henfridsson, O. Investigating the Dynamics of Use Case Construction in Machine Learning Projects. (Under review in an international journal).

- Koukouvinou, P., Holmström, J. & Carroll, N. Sustainability through Normalization: How Sustainability is Enabled and Constrained by Data in Sustainability Initiatives. In Technology and Sustainable Development 2023 (TSD23), *Østfold University College, Halden,* 16 June, 2023.

- Koukouvinou, P. & Holmström, J. Bringing back the role of data in data governance: A critical review and integrative synthesis of the literature. In *Digital Foundations of Business, Operations,*

Strategy and Innovation (DBOSI2023) workshop. Oslo 2-3 February, 2023.

8. Discussion

"*When everything is data, data governance becomes a matter of governance*" (Renieris, 2023, p. 127). In the era of datafication, data governance is increasingly central to how organizations function and how they strive to addressing grand challenges (Davidson et al., 2023; Benfeldt et al., 2020). Davidson et al. (2023), in a recent *Information and Organization* Special Issue, emphasize that data governance is an organizational phenomenon, encompassing both formal structures and informal, everyday practices. This insight resonates with the empirical findings developed in this dissertation. The findings also expose important tensions and blind spots in the literature.

Across the empirical studies, different perspectives revealed how existing data governance frameworks struggled to account for the messy realities of organizations. They also showed how data governance was enacted through everyday data work, shaping and shaped by different socio-technical arrangements. Paper 3 demonstrated how data governance was realized in the making at the *strategic-organizational* level, as organizational actors navigated the tension between protecting the stability of established systems and pursuing digital transformation. This generated challenges tied to the ambiguous nature of data and the emerging pressures of sustainability. Paper 2 complemented this by examining data governance at the *inter-organizational* level, showing how data governance was further complicated due to issues such as lack of trust, intellectual property, and power asymmetries that determine data sharing. Paper 4 extended these insights by shifting to the *operational-practical level*, tracing data journeys across sites to make data work visible in the moments where data flows were either enabled or constrained.

Taken together, the studies moved beyond established data governance frameworks emphasizing formal roles, static policies, and top-down controls (Khatri and Brown, 2010; Tallon et al., 2013). In doing so, they foregrounded every day, situated practices through which data governance was enacted, showing how actors navigated challenges, adapted rules, and co-constructed the conditions for data to flow or stall (Benfeldt et al., 2020; Parmiggiani and Grisot, 2020; Paparova et al., 2023; van den Broek, 2025). This set the stage for the core concern of this thesis: how the capacity of data to move is shaped, enabled, or constrained through the negotiation of frictions embedded in technical systems, institutional contexts, and day-to-day practices. To address this, I return to the research question of this dissertation: *How is data liquidity shaped through the negotiation of data frictions and everyday data work in organizational contexts?*

In responding to this question, I will expand upon and contribute to recent efforts to frame data governance as an evolving and dynamic process (Vial, 2023; Paparova et al., 2023; Benfeldt et al., 2020). I do so by reconceptualizing data governance as an ongoing negotiation between data liquidity and data friction. Echoing Beaulieu and Leonelli's (2022) view of data as dynamic and relational, I define data governance as the ongoing negotiation of how data are produced, validated, shared, withheld, and transformed across organizational practices and infrastructures. Thus, I confirm and expand on prior research that approaches data governance as a situated data practice that emerges through data work (see e.g., Parmiggiani and Grisot, 2020; Grisot et al., 2019). Additionally, I align with research that emphasizes the importance of treating data as a distinctive entity (Kallinikos et al., 2013; Paparova et al., 2023; Benfeldt and Persson, 2025). My thesis advances this perspective by offering empirical insights showing how data governance is enacted in practice. In particular, it engages with Alaimo's and Kallinikos' (2024) argument on the importance of unveiling the

> *backstage process of data creation and use […] and sociocognitive dynamics that emerge from the interplay between data life cycles, technological, infrastructure and novel practices of work.* (p. 86)

In this section, I synthesize the empirical findings to illuminate an integrative view of the nature of data governance and extend understanding beyond what the individual studies have offered. I begin by examining data governance as it is enacted in practice, making visible the data journeys observed across the empirical cases. Building on the findings, I establish the relevance of data liquidity and data friction from the empirical evidence and use them to reflect on and expand the data governance literature. I do so by establishing the relationship between data work, data journeys, data liquidity, and data friction (Section 8.1). I then unpack the socio-technical arrangements that influence data liquidity and may generate data friction (Section 8.2). In Section 8.3, I suggest a conceptualization of data governance, portraying it as an ongoing negotiation between data liquidity and data friction. Lastly, I outline implications for research (Section 8.4) and for practice (Section 8.5).

8.1 Conditions of Data Movement

There is growing interest in how data move across organizational contexts, data infrastructures, and social settings (Priego and Wareham, 2024; Leonelli and Tempini, 2020; Alaimo and Kallinikos, 2024; Vassilakopoulou et al., 2018). In this thesis, I adapt the concept of data liquidity, originating in finance literature (e.g., Fang et al., 2014), to describe the conditions that make such movement possible. Unlike the liquidity of financial assets, which is largely a function of market conditions (Le and Gregoriou, 2020), the liquidity of data is affected by socio-technical arrangements (see Section 8.2 below). Here, I elaborate on two interconnected insights from my work regarding the nature of data liquidity. First, data liquidity is not guaranteed by data quality. Second, data liquidity is not an intrinsic property of data but is produced through data work that involves sense-making, infrastructural integration, and, at times, decisions to preserve a context.

It is tempting to assume that accurate and complete datasets will flow into new contexts with ease. This assumption reflects the optimism that high-quality data will inevitably produce actionable insights (Burton-Jones and Grange, 2013; Mikalef and Krogstie, 2020). Recent research, however, shows why this view is problematic. The ontological instability of data (Kallinikos et al., 2013; Xu et al., 2025; Alaimo and Kallinikos, 2024), challenges fixed criteria for what counts as “good” data. This makes it essential to distinguish between data liquidity and data quality. Data quality dimensions such as accuracy, credibility, completeness, auditability (see Khatri and Brown, 2010; Panian, 2010; Cichy and Rass, 2019; Timmerman et al., 2023), and preventability (Otto and Sadiq, 2013) ensure that data are trustworthy and “fit for purpose” *within* a given context (Strong et al., 1997). Yet data quality dimensions say little about whether they can move *between* contexts, be integrated with other sources, or be repurposed for new uses. This limitation exposes a gap in intrinsic, contextual, and representational data quality dimensions (Wang and Strong, 1996), which largely assume data are objective and static. The limits of conventional data quality measures became evident in Paper 3. In this case, historical forest inventory data were considered complete, accurate when originally collected. Over the years, however, as the forest ecosystem changed, the data failed to represent the forest reality. Therefore, to be used in predictive analytics projects for the NVI, the data required reinterpretation and field validation. This illustrates that *quality reflects the state of data, whereas liquidity reflects their mobility*. Thus, we can deduce that one does not guarantee the other.

Second, data liquidity is not something that data "have," but a condition enacted through data work. In both Paper 3 and Paper 4, making data usable involved work that began at production and continued through interpretation and reuse (see, e.g., Grisot et al., 2019; Parmiggiani and Grisot, 2020). As other scholars have highlighted, this work is collective and ongoing (Parmiggiani and Grisot, 2020; Mikalsen and Monteiro, 2021; Parmiggiani et al., 2022; Aaltonen and Stelmaszak, 2023). In the studied cases, data work took shape through aligning meanings, validating domain knowledge, and negotiating rights of access (Papers 3 and 4). These examples resonate with Mikalsen and Monteiro's (2021) elaboration of ongoing and situated data practices, though the direction is different. In oil exploration, the data work often aims to keep multiple interpretations open, treating uncertainty as a resource (e.g., in prospecting). In contrast, in forest planning, the work focused on sense-making so that data could move across contexts and be trusted in new uses. Put simply, where oil exploration seeks to sustain data ambiguity, forest planning seeks to reduce it. This shows that data work takes different forms depending on what data are expected to do.

Because much of this work is situated, and distributed, it often remains invisible (Alaimo and Kallinikos, 2024; van den Broek, 2025). To make these backstage dynamics more visible, I drew from the concept of *data journeys* (Paper 4 and synthesis). By following data as they move across sites, systems, and actors, I was able "see" the hidden labor that enacts data liquidity (e.g., Leonelli and Tempini, 2020). A key aspect of data journeys is symbolic transformation where photographs, maps, texts, and numerical tables can be combined and used by domain experts (ibid.). In cases, this was evident when remote sensing and field data were used in different types of forest planning. Their symbolic form made them useable and computationally processable (Paper 4). The data journeys also highlight that data rarely travel smoothly. Each movement involves sense-making (Lycett, 2013), reinterpretation, and validation. It is at these points of transfer that data frictions emerge. Interestingly, in my empirical work, data friction did not appear as the opposite of liquidity. Let me unpack this, along with the different ways in which data friction emerged in the findings.

In Paper 4, for example, data friction shifted over time. First, I observed technical friction that arose from the lack of connectivity between ArcGIS and BESK. Data could not circulate across these systems, but they constantly required reformatting and manual work from domain experts. Such frictions are far from exceptional; they are well-documented in the literature as a persistent challenge in the movement of data across heterogeneous systems (Edwards, 2010). Further, I identified that institutional frictions hindered data movement as access to certain datasets required negotiation of rights and permissions (Aula, 2019). Although this slowed down data movement, it ensured accountability and preserved contextual integrity. Such frictions resonate with Bates' (2018) argument that data governance is not only about enabling the free flow of data, but also about setting boundaries around when, how, and by whom data may be circulated. In my cases, it turned out that forest inventory data had to be validated against ecological values before it could be used for predictive analytics models. This slowed data movement but ensured that the data were not moved uncritically. In this way, friction ensured both relevance and legitimacy, showing that delays and interruptions can serve as important checks in the governance of data.

Bringing these concepts together, this work demonstrates *that data liquidity enables data journeys, whereas data friction shows where, how, and why those data journeys slow down or stall*. The three concepts form an interdependent cycle that shapes data governance: data cannot travel without liquidity, and it cannot flow without encountering friction (Edwards et al., 2011; Bates, 2018).

8.2 Socio-technical Arrangements of Data Journeys

Having established the connection between data liquidity, data friction, data journeys, and the practices of data work that sustain them, I now turn to the socio-technical arrangements that affect these journeys. In particular, I highlight four interrelated socio-technical arrangements that shaped the cases I studied: *data sovereignty, asymmetrical power relations, the absence of data strategy, the role of domain knowledge and inconsistencies in the data infrastructure*. This discussion does not aim to be an exhaustive list of all possible conditions identified in the literature but rather reflects empirical observations and draws on wider scholarly debates that help to situate them. I will discuss them here in light of data liquidity and data friction.

Data Sovereignty and Power Asymmetries: Across the cases I studied, many questions and issues emerged related to what I later came to understand through the concept of data sovereignty. The employees themselves did not use this term, but the tensions they navigated over who could access data, under what conditions, and for what purposes resonated with how data sovereignty is discussed in the literature. Recent IS work defines data sovereignty as control and self-determination over data. It encompasses the ability of individuals or organizations to decide how their data are used, shared, and stored, often emphasizing legal, ethical, and technical aspects of maintaining ownership and authority over data assets (Hummel et al., 2021; Von Scherenberg et al., 2024). Data governance literature has focused on ownership, stewardship, and responsibilities, typically assuming stable authority structures (Otto, 2011a; Tallon et al., 2013; Abraham et al., 2019; Black et al., 2023). These contributions are valuable in clarifying who is responsible for data and how accountability can be allocated.

My findings showed that questions of data sovereignty directly shaped how data journeys unfolded. In Paper 2, for instance, collaborative projects were formally framed as venues for openness and knowledge sharing. In reality, however, data movement was negotiated less through formal policy and more through shifts in risk and value. This adds nuance to the findings of Von Scherenbe et al. (2024), who framed data sovereignty as a way to manage trust issues in the face of power asymmetries. My study expanded this by showing how it plays out in practice. In early stages of collaboration, higher trust made data more liquid and data sharing was more open, whereas in later stages, growing doubts led to selective data sharing and data friction. As projects approached commercialization, dominant members of the cluster scaled back their willingness to share, expressing fears of knowledge leakage, intellectual property risks, and competitive threats. This shift restricted data liquidity and introduced data frictions as negotiations, selective data sharing, and infrastructural barriers slowed collaboration and constrained less powerful members. This resonates with the study of Li et al. (2023), showing that even when data ownership formally shifts from those who generate the data to those who manage them, the benefits are not distributed evenly. My findings expanded on this and demonstrated how data sovereignty is continuously enacted but uneven. For instance, for smaller members of the cluster, data sharing and openness were a way to gain legitimacy, an entry ticket to "getting a piece of the innovation pie." For dominant members of the cluster, data shielding and selective data sharing were tools to preserve advantage.

Lastly, in Paper 4, data sovereignty was "revealed" through control over access and interpretation of data. Data friction emerged, here, as a space for reflection and data protection. For example, forest planners decided which data could move and how they should be understood, using their experience and knowledge. This echoes Vassilakopoulou et al. (2018, p. 14), who argued that who owns the data is not predefined but "*fabricated by actors within the arena of action.*"

The Absence of Data Strategy: In my case (Paper 3), data strategy was not articulated in advance. It became visible through its absence. What was revealed was not simply a failure of data liquidity, but that data governance practices were operating without the guidance of an overarching strategy. Within the data governance literature, data strategy is commonly framed as a procedural mechanism designed to align data practices with institutional objectives (Alhassan et al., 2016; Khatri and Brown, 2010; Weber et al., 2009; Alhassan et al., 2018). In the same vein, clear and well-documented policies and procedures can improve the chances of data governance success, with the condition that they must remain flexible (Wang et al., 2025, Alhassan et al., 2018). It is typically positioned as an enabler of data governance that establishes the rationale and structure for how data should be collected, organized, accessed, and managed across the organization (Zhang et al., 2022). The findings from Paper 3 complicate this linear sequencing, revealing that data strategy may emerge from limitations to data governance, rather than preceding it.

In the studied case (Paper 3), despite data governance mechanisms such as quality procedures and access controls, the practices lacked a shared data strategy. What emerged was a cycle of experimenting with AI and analytics potential (objectives of the Sense Project) that failed to turn into a meaningful transformation of work practices. Data became fragmented, incomplete, misaligned with organizational vision, and ultimately "broken," in the terminology of Pink et al. (2018), i.e., failing to retain meaning across contexts. This concern became visible in the predictive analytics project of the NVI (Paper 3). Now, to come full circle back to data journeys, I conclude by quoting Leonelli and Tempini, (2020, p. 11): "*lack of investment and strategy around data journeys implicitly support naïve and unrealistic view as data speaking for themselves, which could compromise the extent to which data that have been mobilized can reliable interpreted as evidence*

The Role of Domain Knowledge and Inconsistencies in the Data Infrastructure: As my findings show, domain knowledge played a decisive role in shaping how and when data moved. Although this was not always explicitly described in the individual papers, the synthesis showed that domain knowledge was essential in contextualizing, validating, and configuring data journeys.

Much of the data governance literature stresses the importance of formalized roles and responsibilities for managing data (Abraham et al., 2019). This is framed as a *locus of accountability* (Khatri and Brown, 2010) and assumes that data governance can be structured around predefined roles and decision-making hierarchies (see section 2.1 and the third wave of data governance for the specific roles). However, my cases (Papers 3 and 4) complicate this picture. They showed that, in practice, domain experts played a significant role in determining what data could travel. Their expertise was critical in contexts where data infrastructure was fragmented and data had to be cleaned and interpreted. This finding both resonates with and challenges current work. For example, Black et al. (2023) highlight the importance of cultivating a *generalist mindset* at the governance level, suggesting that openness and curiosity may sometimes be more valuable than deep expertise. Although my findings support and acknowledge the value of curiosity (Paper 3), they also demonstrate that domain knowledge regarding day-to-day work is irreplaceable (see also van den Broek, 2025).

The significance of expertise became especially visible in relation to temporality and data infrastructures. Leonelli and Tempini (2020) argue that data journeys are inherently spatio-temporal and always in *medias res*, while also noting that "data time" rarely matches "phenomenon time" (see also Mikalsen and Monteiro, 2021). My findings extended these insights by showing that domain experts regulated this mismatch in practice, deciding *when* data were ready to move, i.e., when data could become "more liquid." In my cases, data infrastructure set important conditions, which both enabled and constrained data liquidity. As Edwards (2010) reminds us, data infrastructures are not just neutral backdrops but historically layered socio-technical systems that stabilize certain flows while making others invisible (see also Kitchin, 2014b; Kitchin, 2021). This became evident in Paper 4, where the shortcomings of the data infrastructure required domain experts to act as mediators. This (informal) role echoes recent research on AI management (see van den Broek et al., 2021; Waardenburg et al., 2022).

Reflecting on the socio-technical arrangements that affect data journeys, I want to highlight what can be considered a successful data journey. As described by Leonelli and Tempini (2020), success was not about completion or arrival, but about the qualities that data acquired along the way. This included the ability to move across contexts, to be trusted and taken up by practitioners, and to remain relevant for forestry practice. However, I did not perceive success as being straightforward. On the contrary, I would argue that success was negotiated along the way. With that in mind, I now turn to this negotiation.

8.3 Data Governance in Practice: Negotiating Data Liquidity and Data Friction

My work proposed a reconceptualization of data governance as an ongoing, situated negotiation between the forces that enable data to move and those that constrain them. The need for this reconceptualization arises from a persistent gap between how data governance is theorized and how it unfolds in practice (see also Vial, 2023). The aim is to both acknowledge and challenge dominant traditions that typically portray data governance as a formal, top-down framework designed to secure consistency, accountability, and control (see Section 2.1). They emphasize decision rights, responsibilities, and procedures (Khatri and Brown, 2010; Otto, 2011a; Abraham et al., 2019; Tallon et al., 2013), and often treat data as objective entities (Black et al., 2023; Benfeldt and Persson, 2025).

What these assumptions miss, however, is that *governing data* is a dynamic process that includes both formal mechanisms and everyday practices (Vial, 2023). Data governance, as my empirical work shows, involves continuous adaptation and situated decision-making. I propose an alternative view using the living metaphors of data liquidity and data friction to capture the nature of data governance. From this perspective, I argue that data governance is not the elimination of data friction in pursuit of data liquidity, but the negotiation of their interplay. Framing data governance in this way resonates with concerns in emerging discourses in data studies, where data are seen as mutable, performative, and context-sensitive (Kitchin, 2014a; Kallinikos, 2000; Alaimo and Kallinikos, 2024; Aaltonen et al., 2021; Stelmaszak et al., 2024). My work develops this line of thought by showing that data governance itself emerges through these practices, rather than existing above them. Data governance is thus not external to data work but embedded within it, continually being reshaped as data are produced, moved, and interpreted (Mikalsen and Monteiro, 2021; Parmiggiani et al., 2022; Grisot et al., 2019). My empirical work made this visible. In Paper 4, forest planners and data scientists enacted data governance through situated negotiations over data sharing and data shielding practices. Formal standards such as sustainability goals provided important reference points, but they were always interpreted in light of domain knowledge and context-specific constraints. At times, practitioners relied on instinct or a “gut feeling,” particularly when systems and models failed to capture the complexities of local realities.

Here, I want to focus on the conceptual and analytical significance of data friction. In my work, much like Bates (2018, p. 8), data friction did not simply appeared as "*a frustration to overcome*" or "*necessarily problematic*. Following the author, I approached data friction as emerging through socio-technical arrangements where actors and data infrastructure struggled over how data should move. Further, in alignment with Tomalin (2023), I suggest that *data friction is not always destructive, but can be productive*. It can slow down processes in ways that enable negotiation and reflection. In my case, data friction generated new ways of thinking about "the right kind of data" and understanding the risks of automated processes (Paper 3) (see also Neeley and Leonardi, 2022), and practices of data validation (Paper 4). Data frictions also revealed power asymmetries in the relations between members of the cluster (Paper 2). Aula (2019) observes that *"data frictions are shortfalls only if seamlessness and unhinged flow of data are taken as normative imperatives"* (p. 4). In my case, as Aula (2019) describes, data friction played a role in legitimizing data governance, forcing practitioners to negotiate accountability. To summarize, *rather than viewing data friction as a problem to be minimized and data liquidity as an ideal to be maximized, I suggest that these conditions are relational and co-constitutive, shaped by and shaping the socio-technical contexts in which data work takes place.*

8.4 Implications for Research

This dissertation contributes to the data governance literature by rethinking data governance as a dynamic and emergent process, grounded in the practical realities of how data move or fail to move across organizational, technical, and social contexts. It introduces a novel and practice-oriented approach through the interrelated concepts of data liquidity (Piccoli et al., 2022), data friction (Edwards, 2010; Edwards et al., 2011; Bates, 2018), and data journeys (Leonelli and Tempini, 2020; Priego and Wareham, 2024). I treat these concepts as co-constitutive, unfolding through ongoing negotiation across the data lifecycle and shaping whether data flow or stall. I present data friction as a condition that can sometimes reveal tensions around interpretation, data sovereignty, power asymmetries, trust, strategy, and infrastructural misfit that require active negotiation. Meanwhile, I approach data liquidity as a condition that depends on socio-technical arrangements.

These dynamics reveal that data can be more or less liquid depending on a variety of factors such as interpretation. Together, these concepts make visible the work required to make data actionable (Parmiggiani and Grisot, 2020). This conceptual framing challenges the conventional and rigid approaches that often center on IT governance compliance requirements or predefined data quality metrics (Khatri and Brown, 2010; Abraham et al., 2019; Cappiello et al., 2003; Wang and Wand, 1997). It does so by shifting the analytical attention toward data governance as a situated, negotiated practice, foregrounding what is governed, how, and by whom (Vial, 2023; Paparova et al., 2023). In alignment with prior research, this work perceived data as relational and interpretive, inseparable from the contexts in which they were produced, circulated, and used (Alaimo and Kallinikos, 2020; 2024; Parmiggiani et al., 2022). Such reframing recognizes that data governance spans the full data lifecycle, from data production and sense-making to assessing data and sharing or shielding them (see Alaimo and Kallinikos, 2024). Therefore, it calls for data governance strategies that are adaptive to evolving socio-technical arrangements.

Additionally, this procedural view of data governance has methodological implications. It calls on researchers to attend closely to temporality and situated practices in order to understand how data governance unfolds and how data work evolves over time. Data governance is not enacted once and for all, but negotiated through ongoing, often informal and invisible forms of labor (van den Broek, 2025; Parmiggiani et al., 2022; Benfeldt and Persson, 2025). Yet not all data work enables data movement. Some frictions persist or are even strategically maintained to protect sensitive data. Thus, I stress that studying data governance requires attention not only to efforts aimed at enabling data movement, but also to those that intentionally restrict or reshape it. The concept of data journeys offers an analytical construct for mapping these movements, interruptions, and reconfigurations across actors, infrastructures, and contexts, showing how data governance, much like data (Jones, 2019), is not given, but continuously made and remade in practice. As succinctly put by Leonelli and Tempini (2020):

> *without the ability to track how data change themselves and their environment as they move across contexts, it is impossible to strategize, innovate or even just document data practices and their effects.* (pp. 4-5)

Although this thesis does not focus explicitly on digital transformation, it highlights the role of data governance as a building block for digital transformation. Digital transformation relies on the ability to produce, interpret, and share data in ways that are consistent, legitimate, and trustworthy. The thesis argues that this can be achieved through data governance. In that way, rather than viewing data governance as "something" that precedes transformation in a linear way, the thesis shows that the two should co-evolve. Specifically, data governance shapes what kinds of change are possible, whereas digital transformation efforts expose new data governance demands (Scott and Orlikowski, 2021; Mozaffar and Candi, 2024).

Lasty, in the context AI use, where transparency, fairness, and accountability are central concerns, this thesis demonstrates how data governance enables or constrains the creation of trustworthy systems. It shows that achieving data liquidity requires active effort and that its absence often reflects underlying frictions that must be addressed to ensure responsible transformation. Data frictions can hinder AI use, but they also serve as moments when values, assumptions, and responsibilities are negotiated. Thus, rather than viewing data friction as a failure, this thesis emphasizes the importance of navigating friction as part of building trustworthy AI (see also Janssen et al., 2020). In this way, the findings provide a further understanding of how AI and digital transformation efforts are shaped and limited by the evolving conditions of data governance.

8.5 Implications for Practice

Thinking of data governance as an ongoing negotiation is particularly important for practitioners, as it is often framed in terms of stability, control, and compliance. Practitioners outlets like DAMA-DMBOKv2 emphasize the essentials of data governance, such as planning, quality, stewardship, and data management. Although these are necessary, they offer only part of the picture.

In organizational reality, data rarely just move across sites. Instead, they are continuously interpreted, adjusted, and redefined by those who work with them. Such everyday practices of data work matter, because when overlooked, organizations miss the moments of contextualization that keep data meaningful (van den Broek, 2025). Importantly, when this work is ignored, organizations risk relying on data that do not truly align with the decisions being made (ibid.). Therefore, understanding where and how data work happens opens up possibilities for designing digital tools, AI systems, and processes that reflect how data are actually used and not how they are ideally imagined to flow. Paying attention to this practice also makes it possible to recognize data friction as a meaningful signal. This is because, although data friction hinders data flow, it can also create opportunities for reflection. Therefore, I suggest that managers resist the initial instinct to eliminate data friction. Instead, they can cultivate routines that treat it as a resource. Tools such as "data diaries" (Tkacz et al., 2021) can help understand data assumptions, clarify roles, and expose institutional blind spots. Practitioners aware of these signals are often those who operate between domains, making sense of inconsistencies and adapting practices to make data work in a context. These skills are often underrecognized, yet they are central to effective data governance (see Parmiggiani et al., 2022; van den Broek, 2025). Such skills are valuable for navigating ambiguity, bridging competing perspectives, and aligning theory and practice. Hence, organizations that take data governance seriously must find ways to identify and support this kind of domain knowledge. This involves the cultivation of a digital mindset that embraces the potential of data while understanding their limitations and contextual sensitivity (Neeley and Leonardi, 2022).

Here, a further insight concerns the relationship between data governance and organizational identity. If data governance is treated only as a way to control access or improve efficiency, it risks reducing value to purely technical terms. However, when practitioners question data categories, challenge established assumptions, and reflect on what counts as "good enough data," data governance can take on a more strategic and ethical role. This matters especially for organizations that present themselves as committed to sustainability, social responsibility, or inclusion. The case studies illustrate that sustainability-related data are often uncertain and politically laden. In such a context, effective data governance requires sensitivity to the temporal, ethical, and contextual dimensions of data. Thus, practitioners should not only be concerned with data quality dimensions but also consider whether data support long-term accountability (see Jarvenpaa and Essén, 2023). A key lesson from Holmen is therefore the importance of aligning data work with the temporalities and the context. The forestry sector is shaped by long biological and ecological aspects, such as growth rates, regeneration timelines, and sustainability objectives. Thus, effective data governance in this context cannot be reduced to reports or short-term data insights. Similar challenges arise in other sectors undergoing sustainability transitions, such as agriculture, where data must be governed in ways that promote continuity.

9. Limitations and Future Research

Every study has its limitations. In this final section, I elaborate on the limitations of my work and suggest trajectories for future research (Section 9.1). I also present my visions for my own future research (Section 9.2).

9.1 Study Limitations and Future Trajectories for Data Governance Research

In this thesis, I set out to reconceptualize data governance by challenging its traditional theoretical underpinnings. The concepts of *data liquidity* and *data friction* emerged from the empirical material to capture the messy and negotiated nature of making data usable through everyday data work. They also illuminated the often invisible moments in the data journey where data get stuck or transformed. Still, pretending that my research offers a complete account would be misleading.

The findings of this thesis are based on a sector with long temporal cycles, high dependence on domain expertise, and a strong sustainability commitment. In forestry, the contrast between long-term trajectories and short-term data cycles was always prominent. These characteristics shaped how data liquidity and data friction manifested, particularly the use of data friction as a protective mechanism to ensure sustainability and contextual meaning. Future research could investigate this through targeted case studies in other long-cycle, resource-dependent sectors (e.g., fisheries, mining, and renewable energy) where data flows may be driven more by efficiency than by ecological commitments. Such studies would help determine whether similar socio-technical arrangements occur under other policy frameworks and competitive pressures. In doing so, those studies could refine the applicability and scope of the concepts used here.

Additionally, in this work, I focused on *data work* and how much of it became visible through tracing *data journeys* (Leonelli and Tempini, 2020). By following how data moved, stalled, and transformed across actors and systems (Alaimo and Kallinikos, 2024), I was able to identify points of flow and points of “breaks, stoppages and disjunctures” (White, 2017, p. 93). Still, I am aware that my analysis largely captured *data already in motion*. Other kinds of blockages occur before a data journey even begins. For example, data may be absent because they are never collected or data remain unused. These blockages shape what data journeys are possible, what knowledge shapes decision-making, and whose perspectives are represented. Investigating such “unmapped” or “pre-journey frictions” may offer a promising direction for future research, particularly for understanding how the presence or absence of data influences data work, power relations, and accountability across sectors.

Additionally, this work analyzed data liquidity and data friction as interacting forces in shaping data governance. The empirical material also contained situations that sat between these two conditions (Paper 4 refers to “selective data sharing”). Such practices matter because they show how data governance is actively negotiated as actors balance friction and liquidity. Future research could examine whether such practices remain stable or shift over time, and how policy or organizational changes affect how these practices are carried out and the kinds of data governance frameworks they produce.

Lastly, although this thesis examined the emergence of data governance in practice, it did so within the spatio-temporal boundaries of data journeys (Beaulieu and Leonelli, 2021) that were already visible and active during the study. This meant that slower shifts were not included. For example, control over data can shift from those who produce and contextualize them to those who decide their use, or access and sharing rules can change in ways that give certain groups greater power to shape their interpretation. Such changes reflect shifts in sovereignty, power, and expertise that directly affect how governance emerges. Future research could map socio-technical arrangements of data liquidity and friction over longer periods and across different settings, to capture changes that unfold slowly or in less visible spaces.

9.2 My Own Future Research

Who owns data, and who holds the power to decide when they should move or stay still? To me, these questions are important and deeply topical, touching on the heart of how societies organize knowledge, exercise authority, and distribute responsibilities. Conditions of data liquidity and data frictions are not merely technical or organizational states. As my empirical data showed, they are shaped by –among other things – power asymmetries. Another way to translate these concepts is to see them as *ethical levers*: they determine whose interests are served, whose risks are mitigated, and how values such as fairness and responsibility are embedded in data governance.

In my work, I examined data liquidity and data friction as co-constitutive forces, but I did not explicitly focus on their ethical dimensions (although I inevitably touched on them). This was partly a matter of scope, as the work concentrated on tracing and conceptualizing the conditions through which data governance emerges in practice, rather than making normative claims about what "should" happen. Still, over the course of the PhD work, I developed a growing interest in data ethics, realizing how deeply questions of power asymmetries and responsibility are intertwined and affect the movement of data.

In fact, during my empirical work and my efforts to understand the dynamics of data journeys two interconnected questions kept coming up: does the person who performs the data work also own the data, and what consequences does this have for their liquidity? Earlier in the dissertation, I argued that data sovereignty is shaped through practices of sharing and working with data. Revisiting this now, I see the entanglement of data work, ownership, and responsibility as central. Those who work with data are often not the ones who get to decide how they are used, whereas those who claim ownership may not have done the data work (boyd and Crawford, 2012). This tension raises questions of fairness and responsibility and shapes data liquidity itself. When data sovereignty is separated from the work of producing and using data, it can lead to data friction. Such separation risks mobilizing data in ways that may not truly reflect the intentions of the actors generating them. At the same time, data sovereignty alone does not capture the full picture of control. In fact, having control over data goes beyond just holding rights to include the capacity to supervise, regulate, and make decisions about how data move or are restricted (e.g., Calacci and Stein, 2023). Recent discussions around synthetic data bring these issues into focus. Synthetic data[3] are often presented as solutions to data ownership and control because they allow data to circulate without exposing the "real" data (Liu et al., 2024). In doing so, they appear to reduce data frictions and improve data liquidity. Although synthetic data were not a focus of my empirical work at Holmen, it would be interesting to explore this aspect further, for instance new forms of data friction they introduce (or how they amplify the existing ones).

In my future research, I aspire to expand beyond the organizational scope to investigate questions like:

(1) How does data movement influence decision-making and the way responsibilities are distributed among stakeholders?

(2) How are tensions between ecological protection and the demand for data transparency managed in practice?

These questions align with recent calls in IS scholarship that stress the importance to contribute to more just socio-technical futures (Davison et al., 2022) and to address grand challenges (Davidson et al., 2023). This work can illuminate how the pace, direction, and conditions of data movement shape who benefits from data flows, who is exposed to harm, and how decisions about environmental resources are made and justified. Such an approach recognizes that data liquidity can serve the public good by enabling knowledge exchange. Data friction, in parallel, can be a form of ethical practice, protecting sensitive data from misuse (e.g., Bates, 2018; Aula, 2019). In my future research, I aim to contribute to what constitutes responsible data governance in sustainability contexts.

[3] Holmen began experimenting with synthetic data in autumn 2022 as part of its collaboration with Arboair and AI Sweden (https://www.ai.se/en/news/synthetic-data-and-ai-are-taking-forestry-future). Interestingly, this collaboration did not come up in any interviews.

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Appendix

Business Role	**Overview of Data Work Practices**
Silviculture manager (4 respondents, 4 interviews)	Uses stand-level data (species, growth, density, regeneration) to guide forest planning. Applies laser scanning, satellite data, and inventories to refine thinning and fertilization. Contributes to and interprets models for regeneration and biodiversity, while improving data quality through field validation and collaboration with data scientists.
Head of IT and Analytics (1 interview)	Runs projects that apply forest and operational data. Ensures that analytical results are applied in digital services for forest owners and in decision support for Holmen.
Project manager (1 interview)	Runs projects that apply geodata, satellite imagery, and GIS models in pre-digital forest planning and AI pilots. Ensures that insights from these initiatives are integrated into digital services and decision support.
Innovation leader (1 interview)[4]	Works with customer data, analyzing demographic variables. Uses GPS traces, aerial photos, and laser scanning outputs to test how forest data can support forest planners. Combines, interprets, and evaluates datasets to see what insights they can

[4]The innovation leader and the project manager are the same person, but the roles have different responsibilities and ways of working with data. As innovation leader, the person was involved in the Sense Project. I interviewed this person once in relation to that role and again later in relation to the role as project manager.

	provide, and collaborates with external partners to access high-resolution forest data. Applies design thinking to frame and test data-driven initiatives before handing results to operational teams.
Forestry manager (2 respondents, 3 interviews)[5]	Collects and checks data on planting, clearing(thinning), and land preparation. Records hectares, volumes, and seedling survival. Uses field data from contractors for follow-up. Compiles and summarizes figures for planning, contracting, and reporting.
Delivery coordinator (1 interview)	Uses delivery records and historical volume data to plan yearly timber and pulpwood flows. Runs optimization models to allocate volumes across truck, train, and boat based on transport costs. Inputs purchase estimates from buyers and adjusts the calculated allocations against actual delivery outcomes. Preparing to work with digital planning data to improve efficiency in forest planning.
GIS Architect (1 interview)	Works with geographical and forestry data from field planning, harvesting, transport, authorities, satellites, and property records. Focuses on integrating these datasets, improving update frequency, and ensuring consistent quality. Handles data storage in databases and cloud platforms, and develops strategies to make data accessible and usable across the company.
Marketing assistant (1 respondent, 2 interviews)	Uses data on forest size, ownership location, residence, and past transactions to segment forest owners. Analyzes demographics such

[5]One of the respondents was interviewed twice for complementary purposes.

	as age to define target groups. Produces insights for sales advisors on how to approach different forest owners.
Business developer (silviculture) (1 respondent, 2 interviews)	Uses harvester data to test how harvest leftovers (biomass) affect future operations. Collects and analyzes forest inventory data to assess seedling survival and decide on planting. Interprets operator self-check data to evaluate scarification results. Tests harvesting data to predict what type of trees need to be planted.
Controller (1 interview)[5]	Works with financial and production data. Extracts bookkeeping figures and combines them with harvesting and stock data. Checks costs per cubic meter and identifies errors or deviations. Uses Excel and business intelligence tools to analyze monthly results and ensure that numbers are consistent across systems.
Controller (1 interview)[5]	Uses accounting and business intelligence data to track wood costs and monthly results. Checks contracts, stocks, and harvesting costs, and identifies errors (often from incorrect cost calculations). Follows up deviations, asks buyers or managers to correct entries, and adjusts reports when necessary.
Data scientist (2 respondents, 2 interviews)	Analyzes spatial data from satellites, LiDAR, and harvesters to produce information on forest conditions. Cleans and structures data, applies statistical and ML methods, and validates results with field observations. Generates maps and decision-support material that guide forest planning and operations.

CEO (1 interview)	Provides strategic direction for digital transformation and use of data in forestry.
HR manager (1 interview)	Works with HR databases, safety systems, and digital platforms. Focuses on employee well-being, contracts, and organizational change. Uses data to support HR policies (and also support the vision for digital transformation).
Business developer (1 respondent, 2 interviews)	Works with wood contract data (VSOP), production data (RAPS, BESK), financial systems (Agresso), and Biometria records. Uses ArcGIS Online dashboards and drone imagery to visualize forest conditions. Focuses on combining these datasets to support procurement, customer communication, and operational planning.
Business developer with customer focus (1 interview)	Works with GIS data (maps, satellite images, LiDAR) and drone imagery to monitor forest health and detect bark beetle damage. Integrates GIS with the procurement system (VSOP) to value and purchase wood. Develops applications that connect forest data with procurement processes and customer contracts.
Business manager (1 interview)	Analyzes forest inventory and harvest data alongside sales and contract records to coordinate the distribution of logs to Holmen's mills and external buyers. Applies digital maps and planning systems to support harvesting, logistics, and customer offers. Develops new solutions for private forest owners and focuses on translating customer insights into data-driven services.

IT maintenance manager (1 interview)	Interprets user needs data from forestry staff to improve IT systems. In the Sense Project, collected and analyzed feedback to redesign tract planning processes. Focuses on combining user insights with design thinking to support efficiency and change management.
Expert user (1 respondent, 3 interviews)	Supports timber buyers and applies LiDAR, satellite images, and aerial photos to estimate volumes and detect forest damage. Addresses issues of data accuracy and system integration.
Business developer (forest planning) (1 respondent, 2 interviews)	Updates stand information in BESK, tracks harvesting in RAPS, and uses ArcGIS tools to map forest areas and collect field data. Creates dashboards and reports in Power BI, documents routines for consistent data use.
Forest planner with operational responsibilities (1 interview)	Interacts with BESK and VSOP to plan and harvest. Combines stand data with LiDAR data, satellite images, and field observations to adjust maps, verify volumes, and identify conservation areas. Updates stand boundaries and conditions, prepares maps for production leaders and machine operators, and applies data layers to guide forest management decisions.
Logistic officer (3 respondents, 3 interviews)	Uses VSOP and Lever to track roadside stocks, harvesting status, and deliveries. Coordinates data on volumes, locations, and transport capacity with contractors and production staff to secure timely deliveries and adjust flows between stakeholders.
Area manager planner (1 interview)	Uses BESK, VSOP and ArcGIS field maps to plan thinning and clear-cuts. Combines laser data and field checks

	to update volumes and stand boundaries. Provides operators with maps.
Project manager (1 interview)	Matches operational needs with available data and prototypes solutions. Extracts, analyzes, and interprets harvester production data and other forest datasets using SQL, Power BI, Excel, and ArcGIS Online. Builds visualizations and prototypes for production managers and specialists, while evaluating data quality.
Forest planner (3 respondents, 4 interviews)	Registers and maps protected areas, borders, and access roads in ArcGIS Field Maps. Validates data through observations, then transfers and updates data in VSOP as work orders for harvesters and forwarders. Classifies and documents stands as regards biodiversity.
Raw material manager (1 interview)	Monitors wood flows in VSOP and Lever, validates field data with haulers and production, and adjusts transport plans based on demand and conditions.
Production manager (5 respondents, 6 interviews)	Uses VSOP and BESK to track harvesting and stock levels, validates reported data volumes from contractors and compares with industry delivery data. Prepares data for payments by ensuring alignment between harvesting, transport, and mill reception. Continuously updates and checks data flows to secure reliable supply chain information.
Natural value assessment specialist (1 respondent, 5 interviews)	Collects and structures forestry and sustainability data for reports, validates figures with colleagues, and prepares materials for internal and external communication. Uses data to ensure consistent narratives and to support decision-making.

Business developer, remote sensing and forest data (1 respondent, 2 interviews)	Uses VSOP and BESK data in ArcGIS Online to monitor harvesting, cleaning, and road construction. Collects and analyzes forest data (volumes, tree types, soil conditions), validates with managers, and simulates future scenarios for long-term planning. Supplements with Excel for reports.
Timber economist (3 respondents, 3 interviews)	Inputs and transfers purchase data from buyers into planning systems, configures product specifications, and ensures that machine (harvesting machines) instructions are correct. Collects feedback data from harvesting machines, validates data systems, and tracks changes in product definitions and quality standards. Highlights integration issues.

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Contact person: Professor Christina Keller, Director of MIT, Uppsala University
christina.keller@im.uu.se
Address: The Swedish Research School of Management and Information Technology, Department of Informatics and Media, Uppsala University, Box 513, 751 20 Uppsala
Web site: www.mit.uu.se