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Managing and Making Sense of Data to Drive Digital Transformation: A Case Study

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Completed Research Paper

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Abstract

We explore how organizations manage and make sense of data collaboratively to drive digital transformation. We present the results of an in-depth case study of a financial organization that used Data Operations (DataOps) - a collaborative data management practice to transform its digital-first offering initiative and thereby redefining its value proposition. Drawing on sensemaking theory, we develop a process model that explains how organizations use DataOps to perceive cues through data democratization, extract plausible and comprehensive insights from data through data storytelling to make interpretations, and leverage data products to take actions that drive data-driven digital transformation. Our findings have implications for data-driven digital transformation as we show how DataOps constitutes a new class of data management practices that enable collaboration between data managers and data consumers and allow organizations to make evidence-based decisions to drive their digital transformation.

Keywords: Digital Transformation, Data Management, Sensemaking, DataOps, Analytical Capabilities

Introduction

The world has increased its pace toward a digital economy in which digital transformation is a top priority for organizations (Caleya 2022). Digital transformation is the process in which organizations alter the existing business (e.g., organizational structures, value creation paths, and business models) to enable major business improvements with digital technologies (Verhoef et al. 2021; Vial 2019). Different from IT-enabled organizational transformation, digital transformation involves redefining an organization's value proposition or the emergence of a new organizational identity (Wessel et al. 2021).

Data has emerged as a key strategic asset to drive digital transformation (Kayabay et al. 2022). However, the modern data landscape in this digital age is much more complex, with more sources of data (e.g., Web, open data sources, and commercial data sources), more data use cases (e.g., automation and data science applications), more data flows (e.g., streaming data flow and self-service data flow), and more data consumers (e.g., data scientists, business analysts, report writers, and application developers) (Wells 2019).

Disorganized and poorly managed data can lead to lengthy, laborious, and costly problems that may deteriorate digital transformation progress (Dwivedi et al. 2021). Therefore, managing data is a growing challenge that organizations must address to drive their digital transformations.

Existing literature has explored "data-driven" activities for digital transformation. Bonnet and Westerman (2021) emphasize the importance of data-driven decision-making in digital transformation. Wiesböck and Hess (2019) and Zolnowski et al. (2016) focus on how data-driven innovations impact and enable transformation. Kowalkowski et al. (2022) explore how data-driven services drive transformation and Dremel et al. (2017) highlight a data-driven culture as a critical success factor in digital transformation.

The data-driven digital transformation is a complex process that requires enterprises to revisit their existing data management approaches (Shahi and Sinha 2020). Traditionally, data management focused on managing data volumes, data quality, data security, and data processes (Vidgen et al. 2017). However, in the context of data-driven digital transformation, data management involves more than just ensuring consistent, timely, and high-quality data. It also involves managing the expectations and the ways people understand and use the data to drive new value propositions. As different stakeholders may understand the data differently (Zamani et al. 2020), data management should also ensure data is properly interpreted and used to prevent different interpretations that can lead to communications breakdowns and even contradictory actions between departments, impeding progress towards the transformation objectives (Yeow et al. 2018). To increase the likelihood of success in data-driven digital transformation, organizations need to adopt a collaborative approach to data management. Therefore, we ask: ***How do organizations manage data in a collaborative manner to drive digital transformation?***

We conducted an in-depth case study with a financial organization that used Data Operations (DataOps) (a collaborative data management practice focused on improving the communication, integration and automation of data flows between data managers and data consumers across an organization (Heudecker et al. 2020)) to drive their digital transformation. Drawing on sensemaking theory (Weick et al. 2005), we develop a process model to explain how organizations use DataOps to perceive cues through data democratization, extract plausible and comprehensive insights from data through data storytelling to make interpretations, and leverage data products to take actions that drive data-driven digital transformation. The details of the framework advance the understanding of how firms can address data management challenges and deliver data-driven value propositions. Our findings also advance the utility of sensemaking theory by developing a "data-centric" sensemaking process for data-driven digital transformation.

In the following sections, first, we present the theoretical background of our work. We then introduce the research methodology of our study, followed by the presentation of our findings. Finally, we discuss the implications and limitations of our work and provide a brief conclusion.

Theoretical Background

Managing Data for Data-Driven Digital Transformation

Data management is generally the combination of practices, skills, tools and resources to ensure that data are accessed and delivered to meet the requirements of all applications and business processes (Gartner 2023). Existing literature has highlighted the challenges of data management. For instance: Vidgen et al. (2017)'s study identify data management challenge focal areas, including (1) managing data quality, (2) using analytics for improved decision making, (3) creating a big data and analytics strategy, (4) availability of data, and (5) building data skills in the organization. Shamim et al. (2019) summarize the challenges of big data management in the context of big data decision-making in four dimensions: leadership focus, talent management, technology management, and organizational culture. Ereth (2018) raise the concern of an increasingly complex data environment with heterogeneous tools and technologies, a broad scope with various stakeholders, rapidly changing stakeholder requirements, and a lack of standards.

These data management challenges are further compounded in the context of data-driven digital transformation. For data-driven digital transformation, data should not only be of high quality but also be consumable so that it allows organizations to keep moving forward by making changes in the business (Conboy et al. 2020). Poorly governed, siloed, and disconnected data will impede transformation initiatives and increase the costs and risks of failure in data-driven digital transformation (Judah et al. 2020). Also, as business and technologies change quickly, this fuels the need for data management to adapt to the new

technologies and increase the capacity to meet the business demands of new data and insights (Wells 2019). Data management for data-driven digital transformation needs to characterise data beyond its "big" aspect by delving into granular details of the data and analyzing them in ways that lead to helpful insights (Calvard 2016). It is crucial for organizations to have appropriate practices and skills to interpret the insights in the context of digital transformation and use them collaboratively to drive business changes and actions (Koch et al. 2021). These practices are essential in data management to ensure that organizations fully leverage the potential insights from data and analytics and thereby drive the transformation successfully.

Existing literature conceptualised data management as a technical capability in the context of data-driven digital transformation (e.g., Hansen and Sia (2015) and Rossmann (2018)). In this study, we view managing data for data-driven digital transformation as a socio-technical phenomenon. On the technical side, the right technologies and tools are needed to collect, store, and process data in an efficient and secure way (Kayabay et al. 2022). On the social side, as digital transformation requires changes in organizational culture, workforce skills, and business processes (Hess et al. 2016), organizations need to develop a data-driven culture and coordinate stakeholders to understand, communicate, and use data effectively (Kayabay et al. 2022). The socio-technical nature requires new data management strategies that ensure data is not only secure and of high quality but also used and interpreted across the organization to drive business change (Dremel et al. 2017). However, there is limited literature that explores how organizations can manage and make sense of the data to drive digital transformation in a socio-technical context.

DataOps - A Data Management Approach

DevOps is a software development method that bridges the gap between development and operational teams, enabling organizations to meet the demands of modern, web-based application development and deployment (Palmer 2015). Building on DevOps, DataOps emerged to address the needs of quickly delivering data and accelerating analytics across an organization (Palmer 2015). Although DataOps sounds similar to DevOps, it is not simply applying DevOps to build analytical applications. As emphasized by Kayabay et al. (2022), applying DevOps principles to analytical systems does not guarantee returns because analytical systems differ from software systems. DataOps is a data management approach focused on improving the communication, integration and automation of data flows between data managers and data consumers across an organization (Heudecker et al. 2020). Prior research provided technical solutions for data management, For example, Siddiqa et al. (2016) outline the techniques that provide solutions for big data management (e.g., network management, storage management, pre-processing, processing, classification/prediction, and security management). Huang et al. (2020) suggest a blockchain-based data management approach for digital twin of product. Kuftinova et al. (2022) discuss data fabric technology as an effective data management method in traffic and road systems. Compared with the existing data management methods discussed in literature, the DataOps method is unique because of its socio-technical approach in managing data. DataOps integrates data, people, processes, and technologies in the following ways.

Effective analytics delivery: In data-driven digital transformation, actionable insights are needed to support data-driven decision-making (Dremel et al. 2017). DataOps aims to improve the speed and quality of insights by focusing on automation (Ereth 2018). For example, learning from the continuous integration and continuous deployment (CI/CD) from DevOps, DataOps also uses CI/CD tools to automate the analytical delivery process (Eckerson 2019) and thus improves the effectiveness of analytics delivery for data-driven digital transformation.

Reduce silos: Data-driven digital transformation needs data to be collected and stored in various systems, and data may exist in silos if the systems are not integrated and interoperable (Bergh et al. 2019). Siloed thinking and usage of data across business functions limits its value for data-driven digital transformation (Conboy et al. 2020). DataOps can help to address this issue as it emphasizes cross-functional ownership of data and views analytics as an enterprise endeavor (Atwal 2020).

Enable teamwork and collaboration: A close collaboration between different stakeholders is vital for data-driven digital transformation (Dremel et al. 2017). DataOps adopts the best practices and principles from DevOps and Agile Development (e.g., requiring business engagement and having regular retrospectives) (Eckerson 2019) and focuses on improving the communication, integration and automation of data and analytical workflows between data producers and data consumers (Heudecker et al. 2020).

Research on DataOps mainly focuses on DataOps tools (e.g., (Khalajzadeh et al. 2022)), conceptualization of DataOps (e.g., Ereth (2018)), the relationship between DataOps and business analytics capability (e.g., Naseer et al. (2020)), and the adoption of DataOps (e.g., Rodriguez et al. (2020)). To the best of our knowledge, there is no research that examines the role of DataOps in the context of digital transformation.

Sensemaking Theory

Sensemaking theory describes the ongoing process through which people understand issues or novel and ambiguous events by turning them into a situation that is comprehended explicitly in words and serves as a springboard into action (Weick et al. 2005). Weick et al. (2005, p. 414) conceptualised sensemaking as "a more general progression of organizing - a sequence of ecological change-enactment-selection-retention with the results of retention feeding back to all three prior processes". Specifically, triggered by uncertain or unexpected situations where there is insufficient or inconsistent information, *enactment* process involves noticing, bracketing, and extracting cues about the situation from the environment (Brown et al. 2015). The enactment process results in data with several different possible meanings, of which the number gets reduced in the process of *selection* (Weick et al. 2005). In the selection process, the cues are interpreted to generate a meaningful understanding of the situation (Cristofaro 2022). The interpretations gain further solidity in the *retention* process by informing further actions (Weick et al. 2005).

Sensemaking has been applied in information systems (IS) as a theoretical lens to understand the social, technological, and cognitive aspects of developing, implementing, and using information technologies (IT) (Mesgari and Okoli 2019; Tan et al. 2020). Tan et al. (2020) explain the influence of sensemaking structure, consisting of technical structure and social structure, on ERP implementation. Schoch et al. (2022) adopt the sensemaking theory to: (a) explore user behaviours of digital communications and collaboration tools and (b) identify factors influencing sensemaking and conscious use decisions. Möhlmannn et al. (2023) investigate the algorithm sensemaking process to improve algorithm management.

In the context of data-driven digital transformation, as novel digital technologies are continuously changing competition and consumers (Verhoef et al. 2021), sensemaking offers the processes through which organizations can deal with changing environments and develop response capabilities (Tallon et al. 2019). Existing literature has used the sensemaking lens to study digital transformation in different ways. For example, Pelletier and Cloutier (2019) conceptualise stakeholders' perceptions of IT issues in digital transformation. Penttilä et al. (2020) propose a model with managerial sensemaking frames that influence how managers perceive and interpret the changing environment and the implications for their business. Cárdenas and Esteves (2021) develop a preliminary sensemaking model for digital transformation. Piepponen et al. (2022) identify digital products/services providers and customers' sensemaking practices. In this study, we apply the sensemaking lens in the socio-technical context by exploring how organizations manage data with DataOps and ultimately make sense of data to drive digital transformation.

Research Methodology

We use the case study research method to explore how organizations manage and make sense of data to drive digital transformation. The justification for using the case study method is: a) the aim of this research is to explore and understand a real-world contemporary phenomenon that is hard to investigate separately from its emerging context (i.e., managing data with a DataOps approach to drive digital transformation); b) the research question is a "how" question, which requires an extensive and in-depth description of this social-technical phenomenon (Yin 2018). As little is known about the application of DataOps to manage data in a digital transformation context, we followed an inductive approach to be open to unexpected and new findings (Yin 2018). Below, we introduce the case organization and explain our data collection and analysis process.

Case Selection and Background

A case is the unit of analysis, which is defined as a phenomenon of some sort occurring in a bounded context (Miles et al. 2018). In our research context, the unit of analysis is the organization that uses DataOps to manage its data and thus guide its transformation journey. We bound our case organization by setting the selection criteria as follows: a) evidence of conducting data-driven digital transformation-related initiatives or projects and b) evidence of implementing DataOps-related principles or practices to manage its data.

Using purposeful sampling, we identified a financial organization: GreenFin (pseudonym), which satisfied these criteria. GreenFin is a successful multinational company in the financial sector with more than 32,000 employees, serving millions of customers across personal accounts, small, medium, and large businesses, private clients, and government agencies. To respond to sustainable development goals and create long-term value, GreenFin actively embeds sustainability into its strategy by driving investments in disruptive technologies and partnering with customers in the industry on critical initiatives. GreenFin has made significant investments in its data and analytics capabilities to drive its digital-first offerings initiative. The aim of this initiative is to make customer experiences faster and more seamless by digitising common banking experiences, including simpler unsecured lending offerings, extended eligibility to apply for products digitally, and expanded digital wallet capabilities. GreenFin actively practiced DataOps to manage its data and modernize its data and analytics capabilities. Informed by its data and analytics, GreenFin was transforming its "buy now and pay later" service to redefine its value proposition, that is, making the instalment payment simple and digital for its customers. This gave us the opportunity for an in-depth exploration of how GreenFin managed its data to drive this digital transformation.

Data Collection

A case study relies on multiple sources of evidence, which needs data to converge in a triangulating fashion (Yin 2018). Our research achieves triangulation through the following ways. First, we collected data from multiple sources. The primary data source came from the interviews conducted with experts in GreenFin. We also collected secondary data such as annual reports and public releases (e.g., news and social media posts) related to GreenFin's digital transformation to understand its transformation context, strategy, practices, and outcomes. Second, triangulation is also achieved from the diversity of experts involved in the interviews. We carefully selected experts who had experience and expertise in using DataOps to drive digital business transformation. The interviewees are from different business teams who have overall responsibility for GreenFin's data-driven digital transformation. Table 1 summarizes the data we collected. We mainly used the primary data to develop our framework. The secondary data complemented the primary data by providing additional backgrounds and validating the findings from the primary data.

We developed an interview protocol with open-ended questions that allowed us to probe into participants' responses (Miles et al. 2018). We provide examples of interview questions as follows: Can you please give an example of a digital initiative that is enabled by data and analytics? What are the challenges of managing data in the digital transformation journey? How are you solving those challenges? How is DataOps method applied in your digital transformation? How do stakeholders from different groups and departments collaborate with each other? In total, six interviews (approx. 60-90 minutes each) were conducted. The interviews were recorded and transcribed after seeking permission from the interviewees.

Data Sources	Description		
Primary Data			
Interview No.	Participant Profile	Years at GreenFin	Experience in Data and Analytics
1	Lead Project Business Analyst	3 years	9 years
2	Senior Business Analyst	13 years	13 years
3	Head of Product Analytics	17 years	17 years
4	Head of Digital, Data, and Analytics	18 years	18 years
5	Enterprise Architect	30 years	30 years
6	Executive Private Bank Digital	30 years	30 years
Secondary Data			
Internal Material	Annual reports and annual financial reports; official websites		
External Material	External presentations, blogs on social media, and news		
Table 1. Data Sources			

Data Analysis

Following Gioia et al. (2013), the data analysis process consisted of three stages. In the first stage, the first-order concepts were generated by inductively coding the informant's terms. Specifically, we went through

the transcription and secondary data to identify emerging and recurrent expressions in the data, which described how data was managed and used to drive the transformation at GreenFin. The first-order concepts were generated by giving those expressions labels that retain informants' terms. In this stage, we did not impose prior concepts, constructs, or theories to explain the informants' experiences (Magnani and Gioia 2023). The second stage was to understand the deeper structure of the first-order concepts at a second-order theoretical level (Magnani and Gioia 2023). We combined existing literature and empirical data to sort, reduce, and aggregate the first-order concepts into more abstract second-order themes. In the third stage, the second-order themes were aggregated to form more abstract and aggregated dimensions. Using the sensemaking lens, the dynamic relationships between dimensions were also identified and presented in our framework (see Figure 2), which explained the phenomena under investigation, that is, managing data with a DataOps approach to drive digital transformation.

The first author coded the data and discussed the first-order concepts, second-order themes, and aggregated dimensions with the rest of the authors. The result of the analysis was reviewed by the research team to confirm its appropriateness. The data analysis process occurred via recursive cycling among emergent data, themes, concepts, dimensions, and the relevant literature until no new information was found (i.e., the theoretical saturation was reached) (Gioia et al. 2013). Figure 1 shows the data structure developed after several iterations of analyzing the data from first-order concepts to second-order themes and then to final aggregate dimensions. The data structure shows how the informant-based (first-order) concepts relate to researcher-based (2nd-order) themes and dimensions, which is an important part of demonstrating rigor in qualitative research (Magnani and Gioia 2023).

Findings

Based on our data analysis, we developed the process model shown in Figure 2. Changes in the business environment trigger the need to understand uncertainty and ambiguity through an ongoing process of enactment, selection, and retention. We identify a set of data management practices enabled by DataOps for each stage of the sensemaking process. These data management practices helped GreenFin democratize data to perceive cues, extract plausible and comprehensive stories from data to make interpretations, and deliver data products to drive digital transformations. The results of retention provide feedback to prior processes, helping GreenFin understand the uncertainty and ambiguity inherent in the transformation and thereby respond to the dynamic business environment and redefine its value proposition. We explain the framework through our empirical findings as follows.

Ecological Change

The ecological challenges, slow global economic growth, and high inflation and interest rates have significantly impacted the business environment in which GreenFin operates, which makes GreenFin rethink its business strategies and directions. The business environment is constantly changing. For example, the evolving industry trend and rapid technology changes impacted their customers' behaviors (e.g., increasing usage of mobile devices to manage their banking and financial resources). Moreover, there has been a rise in the number of specialist banking services provided by new competitors who entered the market. Facing the challenges in the business environment, GreenFin's strategic ambition is to serve customers well, remain competitive in the market, and maintain sustainable finance. Driven by these goals, GreenFin has embarked on a digital transformation to provide new value propositions that meet their customers' demands. While the importance and necessity of the digital-first offerings initiative were evident to GreenFin, the changes in the business environment increased the uncertainty and ambiguity of the digital transformation journey, making it challenging for GreenFin to articulate clearly a path towards success.

The **uncertainty** originated because there was not enough information at the start to identify and understand the factors that could influence their digital transformation journey. The Head of Digital, Data, and Analytics noted that: "... *The transformation can be influenced by a number of factors, such as competitive tension in the marketplace, cost, opportunity, or industry trends...and we need to take all these internal and external factors into account*." These factors drove GreenFin to seek actionable information that could guide its transformation journey. The lack of clarity around how to drive digital transformation created **ambiguity**. As the digital-first offerings initiative was cutting across multiple business functions, depending on their role, people in these diverse business functions had different understandings and interpretations of the transformation. Senior Business Analyst stated: "*There would*

be a bunch of people coming in, like from executives or senior level, saying, we want to do this. Then everyone says, yes, that's so nice. We want to transfer from here to here. But these are all like a bit over-ambitious things when you talk in such a big organization."

Figure 1. Data Structure
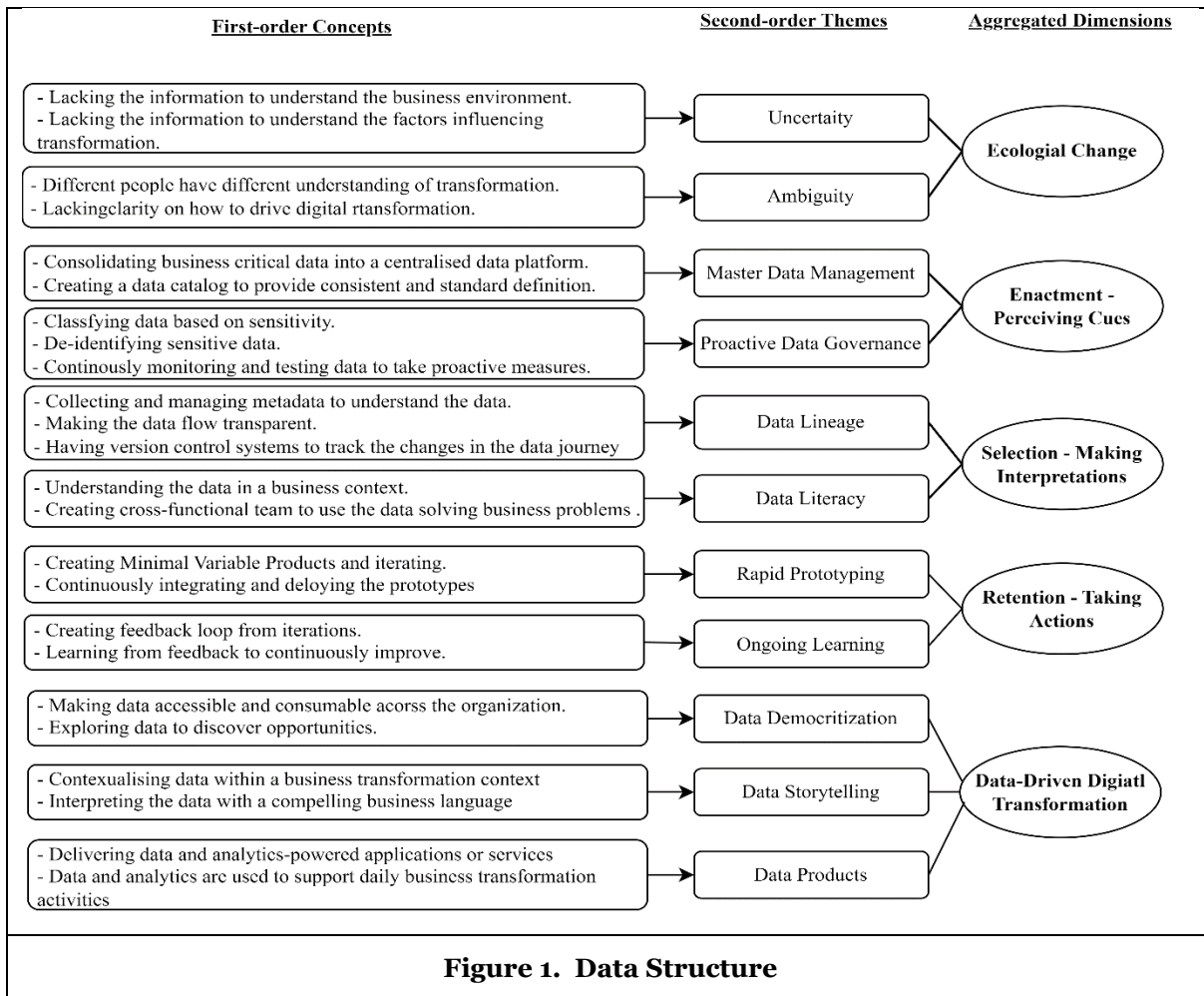
Managing and Making Sense of Data through DataOps

As a large company, GreenFin had many systems that generated and stored data. It would take a long time for users at GreenFin to know what data they could use and where the data was. Moreover, it was also challenging for GreenFin to align all the stakeholders under the same goal. The Head of Product Analytics mentioned: *"So, a lot of my experiences with like highly regulated very conservative very big companies and so often, the challenge is the data exists but who knows where it is who can access it, how do you get permission to access it"*. GreenFin adopted DataOps to manage its data and achieve actionable insights that drove their digital transformation. DataOps provided GreenFin with a collaborative approach to managing its data within a socio-technical context. Technically, GreenFin used tools to continuously test and monitor its data processing. GreenFin also built CI/CD pipelines to accelerate the delivery of analytical solutions. Socially, GreenFin involved their data, IT, and business teams in working iteratively on transformation projects, aligning with the collaborative goals of DataOps. With the DataOps approach, GreenFin has made significant efforts to improve data quality, streamline the process of insights delivery, and bring all stakeholders to work collaboratively. Using the sensemaking lens, we explain how GreenFin addressed the uncertainty and ambiguity in its digital transformation journey and drove its digital transformation journey by managing and making sense of its data with DataOps below.

Figure 2. Managing and Making Sense of Data for Digital Transformation through DataOps – A Process Model
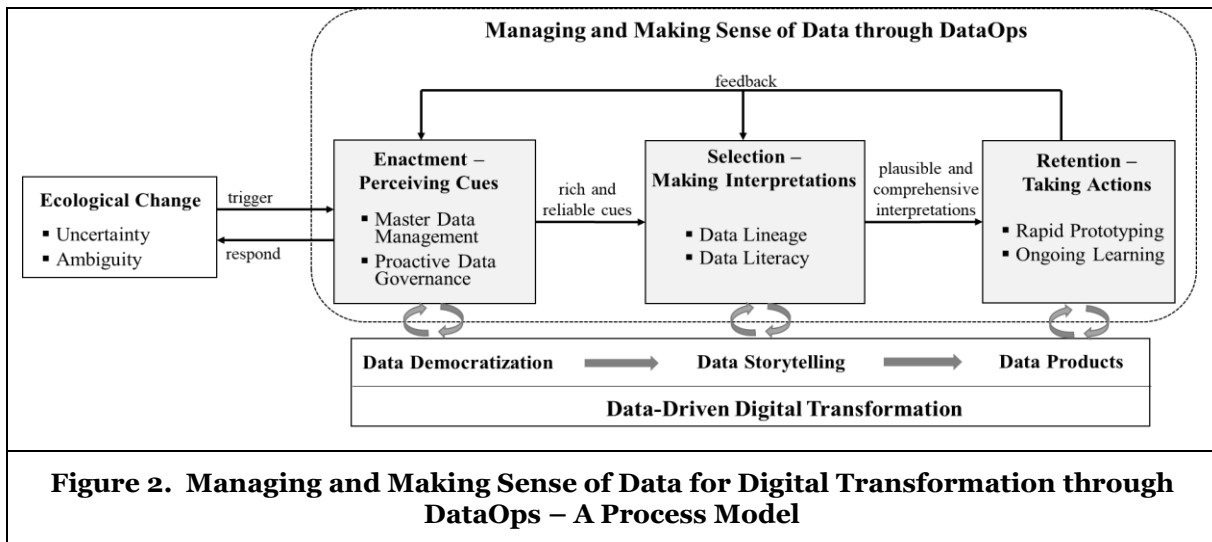
Enactment - Perceiving Cues

To understand the changes in the business environment and take plausible actions (e.g., deliver digital-first offerings) as responses, GreenFin engaged in the process of sensemaking that involved enactment, selection, and retention. The enactment stage started when GreenFin noticed the changes or unexpected situations in the environment. Through the enactment stage, GreenFin collected and explored its data to notice and perceive cues that would help them understand these situations and thereby surface the opportunities and the rationale of digital transformation. The Executive Private Bank Digital in GreenFin provided an example: "*You need to have data to understand what the opportunity is. I remember when I looked at our data and noticed that customers were applying for things like a personal loan on their mobile phones before the mobile phones actually had the responsive design…. So, at the time we saw our customers behaviors changed. They were actually trying to apply these things on these terrible devices. So, we realized that we need to start building a responsive application because we can actually see what customers were doing.*"

As DataOps highlighted the need to provide a consistent understanding of data entities, GreenFin implemented the **master data management** practice to create and maintain a trusted and consistent view of its business-critical data, such as their products and customers, which integrated the fragmented data and removed duplicated data in the organization. GreenFin consolidated all its data from different sources into the Databricks platform and established a data catalog to provide a standard and consistent definition of its master data across the organization. The efforts on master data management allowed GreenFin to get a cohesive and up-to-date view of its business-critical data, enabling GreenFin to perceive its customers' needs, therefore discovering the potential opportunities for its digital first offerings. The Head of Digital, Data, and Analytics mentioned: "*Conceptually, what we're looking to build is what's referred to as a customer's brain. That is an effective analytics engine which gives us a holistic understanding about customers and insights surrounding, what are the most important and relevant things for that customer…. The idea is that data and analytics we are sharing customer information and insights with all of those digital channels.*"

Having **proactive data governance** also enabled GreenFin to perceive cues for digital transformation by removing barriers to data access and monitoring data usage with appropriate controls. At GreenFin, data were classified based on sensitivity, with low-sensitivity data requiring fewer governance processes and being relatively easy to access. However, sensitive customer data were deidentified and pre-calculated according to data consumers' needs. By adopting continuous monitoring and testing from DataOps, GreenFin received alters of any data issues or abnormalities and took proactive measures to address them. With clearly articulated data ownership and data usage policies, the data governance at GreenFin was designed not to restrict people but rather to empower them to do more with data while maintaining appropriate controls. As the Head of Product Analytics explained: "*We need a pragmatic approach to we want to deliver value we want to do it safely rather than kind of the risk-based approach of if we don't do*

anything we don't create more risk which is much easier, I guess, in some ways. Putting the right kind of tools and technologies in the hands of the right people and making access to data different tools, to analyze and report on and deliver outcomes…the risk avoidance side of it. Often, in my experience, this leads you to not extract all the value that's available."

Selection - Making Interpretations

Although GreenFin noticed the unexpected situations (e.g., changing customers' behaviors) from data and perceived cues (e.g., the need to provide digital offerings to its customers) for their digital transformation, simply having this information was not enough to guide them towards the next steps. The cues identified through the enactment stage needed to be interpreted within a broader business context to generate more plausible and meaningful understandings of what digital-first offerings they should provide to satisfy their customers. Senior Business Analyst explained the importance of making interpretations through data as follows: "*We have all the data or all the necessary information. But what we lack is a way to understand and interpret this data and to read it correctly… We should read these patterns, the information, and the analog, and come to a correct conclusion.*"

To better understand the cues and make plausible interpretations, GreenFin adopted DataOps to track the data flow and made the data journey transparent (i.e., **data lineage**). Specifically, the data engineers at GreenFin collected and managed the metadata which provided additional information about their data assets so that data consumers such as business analysts and data scientists understood the data flow. GreenFin also implemented version control systems to automatically track changes in the data journey (e.g., data transformations and analytical models). Such a data lineage capability captured the origins of data, the operations and transformations associated with data, and data destinations, which provided GreenFin with an end-to-end and timely picture of its data and helped data consumers (e.g., business users and decision makers) avoid misinterpreting and misusing the cues for its digital transformation. The Head of Product Analytics summarized: "*DataOps provides us with the process to manage and maintain our data. So, we can know how data get from here to there. We can check that the right data is flowing and then it's consistent and reliable. We can know how the data is moved in the pipelines and between infrastructure.*"

GreenFin also recognized the importance of **data literacy** to interpret the cues. GreenFin provided training to its non-technical users to improve their abilities to read, describe, and use the data in context. DataOps helped reduce the costs for non-technical users to improve its data literacy, because with DataOps, the process of moving data was automated wherever possible. There were also analytical reports in a business language generated automatically, which lowered the threshold to manipulate data and thereby made it simpler and quicker for non-technical users to understand data and make interpretations from it. In addition, GreenFin also highlighted the data literacy of its technical and data experts, which was to improve their understanding of the data in a business context. Following the collaboration principle of DataOps, GreenFin connected and aligned people from different business functions to work with data and learn from each other, improving the data literacy of the whole company. For example, GreenFin organized regular hackathons to improve the employees' understanding of the data and generate ideas of what new value could be delivered to its customers. Executive Private Bank Digital explained this: "*Now we've been doing hackathons in our teams. We will give you data. We will give you a designer, a product owner, and a technical architect. You give us three or four of your people. It's five different teams of each one of us. Then you come up with a problem statement, the solution and the benefits profile for that. It's successful practice because you need data. But you also need insights from people. Without people well understanding how to extract the insights, it will not work.*"

Retention - Taking Actions

In the retention stage, GreenFin acted on their interpretations and evaluated the actions for further improvement. Enterprise Architect explained as follows: "*Our intention is to act on those insights and deliver value to our customers through all of our digital channels, the customer-facing channel, like Internet banking on mobile, or the digital experience for our bankers…It can also be digital marketing, such as email integration and email campaigns that we send out to our customers. The idea is sharing insights with all of those digital channels to make them as effective as possible.*"

To turn the interpretations into actions, GreenFin started to build prototypes for its digital offerings (i.e., **rapid prototyping**). During each prototyping iteration, executive-level managers and different teams including data and analytics team, technology team, and product team worked collaboratively to gather requirements and define a minimal variable product (MVP) for each iteration. The product team led the elaboration sessions to reach a consensus based on the insights extracted from the data storytelling and establish a shared understanding of the products (e.g., new features in their mobile apps) being built and delivered. The continuous integration and continuous deployment (CI/CD) from DataOps helped accelerate the prototype delivery time. Lead Project Business Analyst gave an example of how they did the rapid prototyping: "*Team A has been allocated three days for MVP one, and Team B, we have been given them the next four days and Team C has been given two more days after the four days. So, in total there are nine days. And then there is always a day for integration testing. And in between there's also the testing team, which is always in all the elaboration sessions, because they need to be across all the systems that are going to work together. They're going to conduct the unit testing and then they'll do the integration and system testing as well.*"

Ongoing learning through iterations is the key theme in DataOps. That is why the use of data to learn about the digital-first offering initiative at GreenFin was done in iterative cycles. At the end of each iteration, GreenFin would have a meeting to review and learn what value was required to satisfy their customers. By collaborating with different teams through regular meetings, they shared knowledge and improved their understanding of how the digital offering should deliver value to its customers. Through these interactions, GreenFin was able to continuously learn and improve its transformation journey. Lead Project Business Analyst explained: "*We have several learning cycles within the teams, and we also learn about collaboration and how these particular teams work along. We learn high-tense situations as well. When things go wrong, that basically helps over the next deliveries or the next MVP deliveries. We use our learnings from there.*"

By incorporating the learnings from the retention stage into enactment and selection using continuous feedback loops, GreenFin was able to respond to the uncertain business environment by prototyping new products and services and predicting the changes that may occur in the future. Head of Digital, Data, and Analytics noted: "*Our expectation is we will not only predict future customer behaviors but also track the delivery of our digital features and experiences to ensure that they fit for purposes and meet customer needs.*"

Data-Driven Digital Transformation

The sensemaking process allowed GreenFin to understand its customers, interpret its customers' expectations and needs, and develop and deliver digital offerings that satisfy its customers based on data. Such a data-centric approach drove the transformation at GreenFin that was agile, focused on customers' needs, and manageable. Below, we explain how the sensemaking process informed the data-driven digital transformation at GreenFin.

Data Democratization

During the enactment stage, the data management practices (i.e., master data management and proactive data governance) enabled GreenFin to democratize its data across the company. Specifically, GreenFin collected and managed its master data (e.g., customer data). This helps provide a foundation for consistent, standardized, accurate, and reliable data across the organization and make the data understandable to a wider range of stakeholders. In addition, GreenFin deidentified sensitive customer data, tested the data quality, and prevented data issues proactively to make the data trustworthy and compliant with regulatory requirements. By combining the master data management and proactive data governance practice, GreenFin allowed the data to be used with control and made data as electricity that was always on and consumable for its teams across the organization. These practices removed the walls around data access, giving users greater confidence in the data and facilitating users to explore the data across the organization and better perceive cues for digital transformation. Executive Private Bank Digital described the value of data democratization as follows: "*It gives you something that you can pursue and pick. By picking it, you can then discover opportunities that you may not have noticed before. So that's that is the beauty of it, isn't it? It provides your ability to look at the data, find something that didn't exist before.*"

Data Storytelling

Data democratization allowed data consumers at GreenFin, such as product and operational managers/employees, to access data and recognize the need to deliver digital offerings to customers. However, the data accessed in the enactment stage did not provide GreenFin with a complete picture of what their digital-first offering should look like. To drive the digital-first offerings, data needed to be translated into a comprehensive narrative and compelling business language. Therefore, in the selection stage, GreenFin delved into the data and interpreted the story behind it. The data lineage provided additional context for the data, such as the data origins, collection, transformation, and manipulation for different types of analyses. This additional context of data helped stakeholders understand the data journey and build trust in the insights being presented. Moreover, GreenFin emphasized data literacy for all its employees, including both technical and non-technical users, to contextualize data within the transformation context and ensure a shared understanding of its digital-first offerings. By telling a story behind the data, GreenFin made the data interpretations understandable across the whole company. Head of Digital, Data, and Analytics provided the story of how they approached their transformation from data: "*We use our data and analytics to validate certain hypotheses that we might have around emerging trends and directions that the industry or maybe our own customer segments are heading in. We prove that from advice on perspective surrounding where we are at and what direction or things are selling to move in...If this trend was to continue on its current path over the next 5 or 10 years, as an example. This is what it would mean for our business. We could intervene.*"

Data Products

By democratizing the data and telling stories behind the data in the transformation context, GreenFin became aware of what was happening with its business. In the retention stage, rapid prototyping and ongoing learning enabled GreenFin to develop data products for its digital-first offerings. A data product at Fin 1 referred to a packaged application or service that used data and analytics to solve business problems, improve the business, and thereby deliver new value propositions to its customers. A data product provided a tangible output that retained the understanding gained from the enactment and selection stage. GreenFin rapidly created, integrated, and tested the early versions of its data products to get feedback and iterate on the design. Each iteration provided valuable feedback for the next enactment and selection stage. Throughout the iterative process, GreenFin learned how the product should be evolved to continuously deliver new value propositions for its customers. Head of Digital, Data, and Analytics gave an example of the data-packaged digital offering (as a data product) at GreenFin: "*The buy now pay later we are offering is a pure digital only product that we have brought to market. Because our insights tell us that the way that our customers want to consume that new product digitally. So that's an example of where we have observed industry trends, we have observed appetite from customers, and we have responded to that movement. with a digital product offering to help meet our customers' demands and desires...Of course, once we put the product in the market will continue to run analytics to ensure that that product has the desired effect.*"

Illustrative Example

GreenFin aimed to provide digital first offerings to its customers. However, there were uncertainties and ambiguities at the start. It was not clear what digital services should be delivered to best satisfy its customers and compete in the market. The application of DataOps allowed GreenFin to manage its data in a disciplined way and thereby better understand its data and take actions based on the insights interpreted from data. The transformation initiative "buy now and pay later", as one of the digital-first offerings at GreenFin, is heavily driven by data and analytics. Below, we use it as an illustrative example to put our framework into action (Figure 2). Relevant quotes for this illustrative example are provided in Table 2.

GreenFin's data showed they were impacted by the emergence of disruptive competitors providing new payment methods. There were different systems that generated customer-related data. For example, their product systems included the customers' transaction data. They also had digital channels which generated customers' behavior data. Previously, as data was stored in different places, it was time-consuming to locate and access relevant data. Therefore, GreenFin adopted DataOps to reduce the time and effort to access the data. Specifically, GreenFin centralized all the customer-related data and applied master data management by creating data catalogs, which provided consistent and standard definitions of customer-related data.

Sensemaking Process and Data-Driven Digital Transformation	Example Quotes
Ecological Change	*In the banking industry, there's been a lot of new market entrances: kind of disruptive organizations who are looking to bring specialist banking services to market. (Head of Digital, Data, and Analytics).*
Enactment	*We've got customer data, product and transaction history data. And then we've got digital channels which show customer behavior type data. Typical with most organizations, we have a strategy to put all of that data into a centralized lake and make that available in various forms of conformance and standardization [master data management]. But we also apply quite a number of different techniques to deidentify anonymized data to protect our customers' privacy. And then typically from an analytics perspective, we would use tools like Power BI to visualize the insights and deliver them internally to whether it could be our employees or senior management [proactive data governance]. (Head of Digital, Data, and Analytics).*
Data Democratization	*To understand what's happening within your digital experiences and you need to be creating the appropriate data trials for our employees so that they can then perform and run the appropriate analytics over the top of that data trials to really understand what's going on, what the trends are, and what the opportunities are (Head of Digital, Data, and Analytics).*
Selection	*Having the metadata will help me discover the data better (by providing how the data). From what I can see is that metadata almost determines the success of data [data lineage] (Enterprise Architect).* *From a workforce perspective, we anticipate that we will need to pivot the workforce to have more data and analytics literacy over the journey so that more of our staff members can do self-service analytics to understand the business. [data literacy] (Head of Digital, Data, and Analytics).*
Data Storytelling	*Because our insights tell us that the way that our customers want to consume that new product is digitally. So that's an example of where we've observed the industry trend; we've observed appetite from customers; we've responded to that with a digital product offering to help me our customers' demands and desires (Head of Digital, Data, and Analytics)* *We understand, from a macro perspective, who those players are and what their offerings are. We potentially use various data sources to derive indirectly a view of how much uptake those competitors are getting in the market. So, we can kind of gauge their market traction. Using the visibility that we have from the analytics, we can then determine from a business strategy perspective: what we could or should potentially be doing as a result of that disruption or the change in the market; whether we need to change our offering to evolve to be more relevant in the market, maybe we need to change some of the products and services (Head of Digital, Data, and Analytics).*
Retention	*We start iterating and delivering the digital features that move us towards those targets' side experiences. We also monitor whether features and functions actually are used in the way that we wanted or expected them to and whether they are achieving the original vision or the business purpose that we set out for them to achieve [rapid prototyping] (Head of Digital, Data, and Analytics).* *The process is to progressively understand what we are going to do and adjust based on what we see [ongoing learning] (Head of Product Analysts).*
Data Product	*You might have seen in the press that [GreenFin] is recently bringing a "buy now and pay later" offering to market, similar to Afterpay.... Our business models get impacted by those new market entrants. As a result, we need to adapt our own strategy and our products and services to compete in the market. We performed extensive analytics from our data in the background to ensure that we are in the right place... Of course, once we put the product in the market, we will continue to run analytics to ensure that that product is having the desired effect (Head of Digital, Data, and Analytics).*
Table 2. Example Quotes for the Illustrative Example	

Moreover, GreenFin de-identified customer data by removing customer sensitive information (e.g., name, date of birth, address, and account numbers) to reduce data privacy risks. GreenFin also applied quality assurance tests (e.g., integration test) to the data before delivering the data to its destination. The master data management practice allowed data consumers to access the needed customer information in a much easier and efficient way. In addition, proactive data governance provided secure and reliable data. In such

a way, data was democratized to a wide range of users, which enabled GreenFin to notice an increase in the use of instalment services by its customers.

In the selection stage, by extracting in-depth insights from data and interpreting the insights from a digital transformation perspective, GreenFin found that although increasing numbers of customers were using instalment services, the services provided by its competitors were standalone and lacked integration with other financial services. GreenFin realized the need to provide simpler and more digital instalment services to empower customers with the flexibility to easily manage all their money through the mobile app. This story behind its customers' data could not be built without an in-depth understanding of the data. Specifically, following DataOps' automation principle, GreenFin automated the data delivery process and tagged the data with both technical and business metadata. The metadata provided information such as where and when the data was generated and how it was transformed. Such efforts ensured the lineage of data (i.e., where it came from and how it ended up in the state it was in) was transparent. This transparency helped data consumers understand the data better. Moreover, GreenFin provided training programs and fostered cross-functional collaboration and communications to enrich the understanding of data from different perspectives, improving its employees' ability to interpret the data in a broader context. GreenFin analyzed customers' preferences, usage patterns, and current competitors' products. By communicating the insights with different business units and combining the interpretations from different perspective, GreenFin understood not only its customers' needs but also how they should differentiate themselves with its competitors. As a result, the data was translated into a business narrative in a business plan in which GreenFin extended its existing financial tracking to bring it all together into the mobile application.

In the retention stage, the business plan guided GreenFin to develop a digital solution for the "buy now and pay later" initiative. Aligning with the iterative nature of DataOps, GreenFin aligned its product owner, technology, and data analytics teams to progressively elaborate the key features in each iteration. By continuously learning from each iteration, GreenFin functionally improved the solution through automatically assessing eligibility and checking credit based on historical customer data, allowing its customers to apply and accessing the product in minutes. As a result, GreenFin seamlessly integrated the new digital solution into its mobile application to provide new services to its customers. With the usage of the new "buy now and pay later" feature, more customer data is generated and analyzed to inform the next enactment and selection stage. Technically, the "buy now and pay later" was a data product that relied on its customers' banking and credit history data to support GreenFin in reaching the credit decision in real-time. This represented a shift in GreenFin's business model driven by data and analytics, and was a response to the changes in the business environment.

By managing and making sense of data through DataOps, GreenFin transformed its business both internally and externally. From an internal perspective, the sensemaking process significantly improved the efficiency and effectiveness of data management by removing the data silos, access barriers and aligning the stakeholders under the same goal. From an external perspective, the reliable and well-managed data allowed decision makers at GreenFin to perceive opportunities for its business and redefine its value propositions to its customers in a confident manner.

Discussion

Our findings address the research question by providing a process model that explains how organizations can drive their digital transformation journey by managing and making sense of data using DataOps. In the framework, we identify data management practices (i.e., master data management, proactive data governance, data lineage, data literacy, rapid prototyping, and ongoing learning) and map these data management practices to enactment, selection, and retention stages of the sensemaking process. These data management practices support organizations in democratizing data to perceive cues, extracting plausible and comprehensive stories from data to make interpretations, and delivering data products to drive digital transformations. Below, we provide the implications of our findings for research and practice.

Implications for Research

This study provides contributions to research in several ways. First, our findings contribute to digital transformation research. Aligning with Wessel et al. (2021) who suggested digital transformation involves

redefining value propositions, our research provides empirical evidence on how companies can redefine the value propositions by managing and making sense of their data in a disciplined and collaborative manner. Indeed, existing research has explained the importance of data management in digital transformation (e.g., Dremel et al. (2017)) and conceptualized data management as a technical capability required in digital transformation (e.g., Hansen and Sia (2015)). Our findings extend the existing literature by providing a socio-technical perspective on data management in the context of digital transformation. Our findings highlight the collaborative nature of data management and provide potential solutions to address the data management challenges (e.g., data silos and long waiting time). Our findings also emphasize that data management relies on not only techniques but also human capabilities to understand and interpret data collaboratively, ensuring that data can drive new value propositions.

Second, this study contributes to DataOps research. Existing literature has emphasized DataOps as a data management method and explained the goals of DataOps (Ereth 2018; Heudecker et al. 2020). Our research enriches the conceptualization of DataOps by adding the data-driven digital transformation context. We provide empirical evidence of how DataOps is used to manage data and drive digital transformation. Besides, there is literature focusing on the technical aspects of DataOps (e.g., Khalajzadeh et al. (2018)). Our research enriches DataOps conceptualization by highlighting its socio-technical features that enable organizations to combine people, processes, technology and data to drive digital transformation.

Third, our findings also contribute to the sensemaking theory. Our findings bring novel insights by introducing a new form of sensemaking – data-centric sensemaking. We elaborate on the enactment, selection, and retention model introduced by Weick et al. (2005) in the context of data-driven digital transformation. Existing research has identified key features of the sensemaking process, such as focusing on extracted cues, plausibility over accuracy, social, and retrospective (Kudesia 2017; Weick et al. 2005). Our findings refine these features for data-centric sensemaking. Specifically, data-centric sensemaking is: (1) focused on data because business data provides cues and is the raw material that fuels interpretation; (2) driven by both plausibility and accuracy because on the one hand, organizations require high-quality data and analytics to understand their business more precisely. On the other hand, data and analytics do not provide absolute accuracy and certainty. Actions are based on plausible interpretations and will evolve with more feedback generated; (3) sociotechnical because from a technical perspective, technologies are needed to automate analytical delivery to deliver cues. From a social perspective, data-centric sensemaking also needs the interaction and collaboration among different stakeholders (e.g., data experts, business users, and technical experts, and executive-level managers); (4) retrospective and prospective because on the one hand, historical data is collected and analyzed to help organizations understand the past events and circumstances. On the other hand, analytics techniques such as predictive analytics can provide prospective and forward-looking insights for future actions.

Implications for Practice

Our research highlights the importance of data capture and accessibility in driving digital transformation. As the data provides cues for transformation and serves as the foundation of further actions, organizations should strive to capture an adequate range of data sources to expand the data coverage of the business. Additionally, while ensuring data compliance and protecting data security is important, organizations should not overly restrict data access and usage. Instead, organizations need to balance the risks and value of data, ensuring that data is accessed with appropriate control.

Our research also emphasizes data management as a collaborative effort across the entire organization. The data management practices identified in this study require the whole enterprise to work together and view data as an organizational asset for transformation. For example, master data management practice requires the effort of data owners in different business units to integrate the data across the organization. Data literacy is not only crucial for business users to enhance their ability to understand and utilize the data, but it is also necessary for technical people to improve their understanding of the transformation context behind the data communicates data in a way that is understandable across the organization. Data storytelling also indicates the collaborative nature of data management. Because of data storytelling, stakeholders could reach a consensus of interpretation of data, which guides further actions. Adopting these data management practices can help align the different stakeholders to address the complexity of data-driven digital transformation by managing and making sense of data in a disciplined way.

Besides, our findings suggest that sensemaking in data-driven digital transformation is an ongoing process, and managers need to define appropriate metrics and continuously measure them during the transformation journey to ensure they are on the right track. There is also a need to establish feedback mechanisms that enable organizations to maintain and evolve their data products to meet the transformation needs continuously.

Conclusion, Limitations, and Future Research

In this paper, we explain how organizations manage and make sense of data with a DataOps approach for data-driven digital transformation. Based on the case study of a company in the financial industry, we develop a process model that identifies key data management practices that underpin the sensemaking process of enactment, selection, and retention to drive digital transformation. These data management practices enable organizations to democratize data, extract plausible and comprehensive stories from data, and deliver data products to drive digital transformation.

Our research has several limitations. First, although we designed the research carefully and had access to diverse experts, we acknowledge that our data came from only six interviews in one company. This limits the generalization of our findings to other contexts. Moreover, our interviewees are mostly senior level managers, which may create potential bias. In addition, we recognize that we do not consider the factors that may influence the adoption of DataOps in managing data for data-driven digital transformation. For example, different industries have different levels of data regulatory compliance, which could lead to different strategies and orientations for data management. Also, organizations with different technological maturity may implement DataOps differently to manage their data.

Future research can conduct multiple case studies with more data to further develop and deepen the process model. Future research can also conduct interviews with less experienced people to understand how DataOps cater their needs for data and analytics. In addition, future research can further identify the factors such as industry and existing technical capabilities that affect the utility of DataOps in managing data for digital transformation. Furthermore, as data democratization, data storytelling, and data products are the key components in data-driven digital transformation, future research can further explore these concepts in more depth or investigate other crucial building blocks required for data-driven digital transformation.

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