



**UNIVERSITY
OF TURKU**

Turku School of
Economics

Onboarding Business Domains into a Data Mesh

A Kotter-Based Change Enablement Framework Tested at Toyota Motor Europe

Master's thesis

Author:

Xavier Kasdan

Supervisor:

Dr Ulrich Laitenberger

05.06.2025

Brussels

The originality of this thesis has been checked in accordance with the University of Turku quality assurance system using the Turnitin Originality Check service.

Master's thesis

Subject: Data Mesh Implementation

Author(s): Xavier Kasdan

Title: Onboarding Business Domains into a Data Mesh: A Kotter-Based Change Enablement Framework

Tested at Toyota Motor Europe

Supervisor(s): Dr Ulrich Laitenberger

Number of pages: 66 pages + appendices 4 pages

Date: 05.06.2025

Abstract

As organisations adopt decentralised data architectures like Data Mesh, many struggle to operationalise new roles such as Data Product Owner or Domain Data Steward. While technical aspects are well-documented, the organisational and behavioural dimensions, particularly the onboarding of business stakeholders, remain underexplored. This thesis investigates how large enterprises can enable successful role adoption during a Data Mesh transformation. Based on a qualitative case study at Toyota Motor Europe and using abductive reasoning, the study proposes the Data Mesh Change Enablement Framework, an adapted eight-step change model inspired by Kotter's theory but tailored to decentralised contexts. The framework emphasises contextualised urgency, multi-level coalitions, co-created role narratives, peer-driven acceleration, and institutional anchoring. Grounded in empirical data, the framework offers a practical yet flexible tool for guiding change in large-scale data transformations.

Key words: Data Mesh, Change Management, Decentralised Data Governance, Business Stakeholder Onboarding, Data Product Owner, Federated Architecture, Kotter's 8-Step Model, Qualitative Case Study, Toyota Motor Europe.

TABLE OF CONTENTS

1	INTRODUCTION	8
1.1	Context and Problem Setting	8
1.2	Research Motivation and Gap	9
1.3	Research Aim and Questions	10
1.4	Structure of the thesis	11
2	LITERATURE REVIEW AND THEORETICAL FRAMEWORK	12
2.1	From Centralised Architectures to Decentralised Data Mesh	12
2.1.1	Data Warehouse	12
2.1.2	Data Lake	13
2.1.3	Data Lakehouse	14
2.1.4	Data Mesh	15
2.2	Data Mesh Principles and Their Organisational Implications	16
2.3	Change Management in Data and Digital Transformation	18
2.4	Comparing Change Management Models (Lewin, ADKAR, Kotter)	19
2.4.1	Lewin's 3-Step Model	19
2.4.2	Kotter's 8-Step Model	20
2.4.3	ADKAR	21
2.4.4	Framework Comparison	22
2.5	Justifying Kotter for Data Mesh Transformations	22
2.6	Identifying the Research Gap	25
3	RESEARCH METHODOLOGY	27
3.1	Research Design	27
3.2	Data Collection	28
3.3	Data Analysis	30
3.3.1	Abductive Reasoning and Thematic Coding	30

3.3.2	Triangulation	30
3.4	Research Quality	31
4	EMPIRICAL FINDINGS: DATA MESH IMPLEMENTATION AT TOYOTA MOTOR EUROPE	32
4.1	Organisational and Data Context	32
4.2	Mapping Empirical Findings to Kotter's 8-Step	34
4.2.1	Step 1: Create a Sense of Urgency	34
4.2.2	Step 2: Build a Guiding Coalition	35
4.2.3	Step 3: Form a Strategic Vision and Initiatives	37
4.2.4	Step 4: Communicate the Vision	38
4.2.5	Step 5: Empower Broad-Based Action	40
4.2.6	Step 6: Generate Short-Term Wins	41
4.2.7	Step 7: Sustain Acceleration	43
4.2.8	Step 8: Institute Change	43
4.3	Emergent Challenges and Enablers	44
4.3.1	Tensions in Ownership and Motivation	45
4.3.2	The Business-IT Divide	45
4.3.3	The Complexity of Data Products	46
4.3.4	The Organic Nature of Change	47
5	DISCUSSION AND FRAMEWORK DEVELOPMENT	49
5.1	Deriving the Framework	49
5.2	The Data Mesh Change Enablement Framework	49
5.2.1	Step 1: Reframe Urgency	50
5.2.2	Step 2: Build a Multi-Layered Coalition	51
5.2.3	Step 3: Materialise the Vision	52
5.2.4	Step 4: Translate the Message	53
5.2.5	Step 5: Empower Domains for Ownership	53
5.2.6	Step 6: Showcase Early Wins	54
5.2.7	Step 7: Institutionalise Learning Loops	55
5.2.8	Step 8: Embed New Roles in Governance	56
5.3	Validation and Practical Implications	57

5.3.1	Empirical Grounding	58
5.3.2	Framework as a Practical Tool	58
5.3.3	Boundary Conditions	59
6	CONCLUSION	60
6.1	Answering the Research Questions	60
6.2	Limitations	61
6.3	Directions for Future Research	62
6.4	Final Reflection	62
	REFERENCES	64
	APPENDICES	67
	Appendix 1 – Interview Guide	67
	Appendix 2 – Extracts from Interviews	68
	Appendix 3 – AI Usage	70

LIST OF FIGURES

Figure 1 – Kotter’s 8-Step Model	23
Figure 2 – Evolution of Step 1	50
Figure 3 – Evolution of Step 2	51
Figure 4 – Evolution of Step 3	52
Figure 5 – Evolution of Step 4	53
Figure 6 – Evolution of Step 5	54
Figure 7 – Evolution of Step 6	55
Figure 8 – Evolution of Step 7	56
Figure 9 – Evolution of Step 8	57
Figure 10 – The Data Mesh Enablement Framework	57

LIST OF TABLES

Table 1 – Interviews characteristics.....	29
Table 2 – Interview Guide	67
Table 3 – Extracts from Interviews	68

1 Introduction

1.1 Context and Problem Setting

Over the past two decades, organisations have experienced an exceptional increase in the volume, velocity, and variety of data they produce and consume [1]. The growth of connected devices, digital transactions, and sensor-based technologies has driven this exponential growth, leading to projections that the global volume of digital data will exceed 221 zettabytes by 2026 [2]. This large increase in data has fundamentally reshaped how companies perceive information, not merely as a by-product of operations but as a critical strategic asset with the potential to create value across all levels of the enterprise [3].

In response to these changes, organisations have historically relied on centralised data architectures such as Data Warehouses (DWH) and Data Lakes (DL) to manage and use their data assets [4]. While enabling consistency and control, these models have struggled to keep pace with modern business demands. One of the main problem related to central data teams who often become bottlenecks, lacking the domain-specific knowledge to deliver high-quality, context-sensitive data products [5]. These limitations have revealed a growing mismatch between the complexity of organisational data needs and the capabilities of centralised management structures.

Introduced by Zhamak Dehghani in 2019, the concept of Data Mesh represents a paradigm shift. It moves beyond centralised, monolithic systems to propose a decentralised architecture based on four key principles: domain-oriented ownership, data as a product, self-serve data infrastructure, and federated computational governance [6]. By assigning data ownership to the team that understands it best, Data Mesh promises scalability, responsiveness, and greater contextual relevance.

However, implementing Data Mesh is not simply a technical upgrade; it requires a profound organisational transformation. Business domains must assume new roles, such as Data Product Owner and Domain Data Steward, that challenge existing norms, skills, and responsibilities [6]. These shifts are not only operational but also cultural, demanding changes in mindset, incentives, and coordination. In the absence of clear enablement structures, organisations risk uneven role adoption or confusion and the stagnation or failure of the transformation effort.

While architectural strategies for Data Mesh have been widely explored, the human side of the transformation remains poorly understood. In particular, there is limited research into how business stakeholders are supported in adoption of these unfamiliar roles. This lack of insight has serious

consequences: unclear responsibilities, disengagement from business domains, and re-centralisation tendencies that undermine the decentralisation goal. Without role clarity, training, and change management, the promise of decentralised data ownership may remain a utopia.

1.2 Research Motivation and Gap

While the principles of Data Mesh have been widely discussed in conceptual literature and industry blogs, the conversation remains largely centred on technology (frameworks, pipelines, and governance mechanisms) [7], [8], [9]. What is still missing is a systematic exploration of the people side of the transformation: how organisations reshape roles, skills, incentives, and culture so that Data Mesh can succeed in practice.

During a six-month internship at Toyota Motor Europe, a leading industrial firm undergoing a Data Mesh transformation, this challenge emerged as a central concern. Through direct observation and interviews with stakeholders from both IT and business domains, it became clear that the difficulty was not in understanding the conceptual framework of Data Mesh. Rather, the struggle lays in operationalising it, and more specifically, in helping business stakeholders appropriate their new roles and assume ownership over data assets. Many were unclear about their responsibilities as Data Product Owners or Domain Data Stewards and were hesitant to embrace new accountabilities that fell outside their traditional scope of work.

This disconnection between architectural ambition and organisational reality highlights the need for a structured change management approach tailored to Data Mesh. Although practitioner literature often acknowledges these human challenges, academic studies remain scarce. Case evidence is largely drawn from grey literature, such as blog posts and conference talks, while academic contributions have focused predominantly on technical architectures, governance models, or platform design [10], [11], [12]. A review of current literature conducted in Chapter 2 confirms that no existing academic work has systematically analysed role enablement or onboarding in the context of Data Mesh implementation.

Most strikingly, no academic study has applied a formal change management framework to a Data Mesh implementation. This thesis addresses that critical gap by integrating Kotter's 8-Step Process for Leading Change [13] with empirical findings from Toyota Motor Europe. It aims to investigate how structured change strategies can support business domain stakeholders in taking on new data roles and to develop a theoretically grounded, practically useful framework for organisations undergoing similar transformations.

Thus, this research is motivated by two factors. On the practical side, many organisations pursuing Data Mesh encounter resistance, confusion, and misalignment due to the novelty of the roles and the lack of adequate support structures. On the academic side, this study responds to a pressing need for empirical research that connects organisational change theory with the practice of decentralised data architectures.

1.3 Research Aim and Questions

This thesis explores the organisational dynamics involved in implementing a Data Mesh architecture. It focuses on how business domain stakeholders are onboarded into new roles such as Data Product Owner and Domain Data Steward. Although Data Mesh is often promoted as a technical solution to issues like scalability, agility, and interoperability, its success relies heavily on organisational change. In particular, it depends on the ability of business units to take on responsibilities that were traditionally handled by centralised data teams.

Rather than evaluating Data Mesh as a technology or comparing architectural paradigms, this study focuses on the human and organisational shift involved in decentralising data ownership to the business. This process is examined through the lens of change management theory, using John Kotter's 8-Step Process for Leading Change as the primary analytical framework. Through a qualitative case study of Toyota Motor Europe, an organisation actively experimenting with Data Mesh at scale, this research explores the barriers, enablers, and change strategies involved in building distributed data capabilities.

The following research question guides this thesis:

Main RQ: How can organisations effectively manage the onboarding of business-domain stakeholders into their new roles and responsibilities during a Data Mesh implementation?

To address this overarching question, the study explores four interrelated sub-questions:

- **RQ1:** What organisational challenges emerge when onboarding business teams into decentralised data ownership roles?
- **RQ2:** How do business stakeholders understand, embrace, or resist the roles of Data Product Owner and Domain Data Steward?
- **RQ3:** In what ways can Kotter's 8-Step Process be adapted to address the organisational challenges of Data Mesh implementation?

- **RQ4:** What organisational enablers, beyond technical infrastructure, support the sustained adoption of these roles across domains?

These questions are designed to generate both theoretical insight and practical guidance for addressing the human side of Data Mesh transformation.

1.4 Structure of the thesis

This thesis is structured into six chapters, each contributing to investigating how business stakeholders can be effectively onboarded into decentralised data roles during a Data Mesh implementation.

Chapter 1 introduces the research topic, outlines the practical and academic motivations behind the study, defines the central research question and sub-questions, and presents the overall structure of the thesis.

Chapter 2 presents a literature review covering the evolution of data architectures, the principles and organisational implications of Data Mesh, and existing management frameworks. It also justifies the use of Kotter's 8-Step Process and highlights a gap in current academic research regarding role enablement in decentralised data contexts.

Chapter 3 outlines the research methodology, including the abductive case study design, data collection through semi-structured interviews at Toyota Motor Europe, and the analytical strategy used to code and interpret the data. It also discusses research quality criteria.

Chapter 4 presents the empirical findings from Toyota Motor Europe, first mapping them to Kotter's 8-Step Process, then highlighting challenges that extend beyond it such as tensions in ownership, the business–IT divide, and the organic nature of change.

Chapter 5 builds on these insights to develop the Data Mesh Change Enablement Framework, adapting Kotter's model to decentralised contexts with concrete steps to support role onboarding and legitimacy.

Chapter 6 answers the research questions, outlines limitations, and proposes directions for future research. It reinforces the framework's practical and theoretical relevance, while situating it within broader organisational dynamics.

2 Literature Review and Theoretical Framework

2.1 From Centralised Architectures to Decentralised Data Mesh

2.1.1 Data Warehouse

Data Warehouses (DWH) emerged in the 1990s as a foundational architecture for analytical data processing. They integrate structured data from various sources using a schema-on-write approach, where data models must be predefined before ingestion. This ensures consistency, quality, and performance for business reporting and analysis [4], [14].

DWHs rely on the Extract-Transform-Load (ETL) paradigm, which extracts data from source systems, transforms it to fit a unified schema, and loads it into a central repository. The architecture also separates transactional and analytical workloads to avoid performance degradation on operational systems [14], [15].

DWHs enabled rapid execution of complex analytical queries through technologies like OLAP (Online Analytical Processing) cubes, allowing multi-dimensional data analysis. They were designed to serve many concurrent users with interactive querying capabilities, making them the central analytical asset in many organisations [4], [14].

Despite these advantages, DWHs faced critical limitations as data sources grew in volume and diversity. First, the architecture is not well-suited to unstructured or semi-structured data such as XML, JSON, audio, or images. These require significant transformation to fit rigid schemas, often resulting in data loss or oversimplification [4], [15]. Second, the batch-based ETL process introduces latency, with some data only becoming available after a day or more, which is too slow for modern real-time analytics needs. Third, the rigidity of the model means that adding new data sources or fields can take months, discouraging agility [15].

Furthermore, the centralised nature of DWH management (where data requests and transformations must be handled by a central team) has become a bottleneck in large organisations. This team often lacks the domain knowledge to provide context-rich data products tailored to business needs, which has further fuelled dissatisfaction and delayed data-driven initiatives [16].

These architectural and organisational challenges laid the foundation for the emergence of more flexible and scalable models, such as Data Lakes, which promised to store all types of data with fewer upfront constraints.

2.1.2 Data Lake

The Data Lake (DL) emerged as a response to the rigidity and limitations of Data Warehouses, particularly their inability to efficiently handle large volumes of diverse data formats. Conceptually, a DL is a scalable storage repository that ingests and stores raw data in its native format, whether structured, semi-structured, or unstructured, until it is needed for analysis [17]. Unlike DWs, which impose a strict schema at the point of ingestion (“schema-on-write”), Data Lakes adopt a more flexible “schema-on-read” approach, meaning structure is only applied when the data is queried [14].

This architecture allows organisations to store virtually unlimited volumes of data, including real-time streams from sensors, devices, and social platforms. The absence of rigid schemas at ingestion facilitates agility, as data of all types can be ingested without needing to first define its structure or destination [17]. Furthermore, by separating storage from compute, Data Lakes support more cost-effective and scalable analytics infrastructures [18].

Technically, Data Lakes are architectures where data is stored in a central repository, often on distributed file systems like HDFS (Hadoop Distributed File System). These systems replicate and partition data for durability and scalability, enabling fast ingestion and high availability [14].

The flexibility of the model, however, introduces new challenges. As organisations adopted the “store everything” strategy, many Data Lakes turned into ungoverned, undocumented repositories, often referred to as “data swamps”, where finding trustworthy and usable data became difficult [4], [19]. The absence of strong metadata management, version control, and lineage tracking made it difficult for users to understand what data was available, what it meant, or whether it could be trusted [19].

Another problem was data quality. Since Data Lakes allow raw ingestion, many datasets are not cleansed or harmonised, and multiple, conflicting versions may coexist. Without consistent governance, organisations often find themselves facing the same bottlenecks as in Data Warehouses, just now distributed across an even messier landscape [15].

To counter these issues, some Data Lakes introduced semantic layers or hybrid architectures that tried to incorporate elements of data governance and data management. But even with these improvements, the lack of inherent structure and clear ownership made it difficult for many users to turn data into usable, scalable solutions. These shortcomings led to the emergence of new paradigms, including the Data Lakehouse and, eventually, the more organisationally transformative Data Mesh.

2.1.3 Data Lakehouse

The Data Lakehouse represents an architectural convergence between the flexibility of Data Lakes and the reliability and governance of Data Warehouses. It emerged as a response to the shortcomings of both preceding paradigms: while DLs offered scalability and cost-effectiveness, they suffered from governance and quality issues; and while Data Warehouses ensured structured consistency, they lacked the flexibility needed for modern data volumes and types [15], [18].

A Data Lakehouse architecture enables both traditional business intelligence (BI) and modern machine learning (ML) on a unified platform. It leverages the cost efficiency and schema-on-read capabilities of Data Lakes while introducing ACID-compliant (Atomicity, Consistency, Isolation, and Durability) transactions, schema enforcement, and governance mechanisms that were traditionally reserved for Data Warehouses [15].

One of the defining characteristics of a Lakehouse is its use of open data formats. These formats allow concurrent read/write operations, enforce schema consistency, and enable advanced features such as versioning, time travel, and partitioning. Unlike traditional pipelines, where data is repeatedly copied between layers (e.g., from lake to warehouse), a Lakehouse enables direct access by multiple engines, thus reducing duplication and latency [20].

Critically, Lakehouses offer improved governance and quality. They include catalogue and metadata services, enforce access controls, and manage schema evolution dynamically. These capabilities resolve many of the issues that undermined early Data Lakes, such as outdated data, version confusion, and lack of accountability [20].

Nonetheless, it is worth noting that the Lakehouse, while technically sophisticated, does not fundamentally shift the centralisation paradigm. Governance, ownership, and operational responsibility often remain in the hands of a central data team, reintroducing bottlenecks, limiting scalability, and distancing data producers from those best equipped to manage and improve their

data. This has prompted some organisations to look beyond the Lakehouse to decentralised models like Data Mesh, which aim to redistribute data responsibilities across business domains.

2.1.4 Data Mesh

Building upon the lessons and limitations of centralised architectures such as Data Warehouses, Data Lakes, and Lakehouses, the Data Mesh emerges not simply as a new architectural model, but as a socio-technical paradigm shift. Introduced by Zhamak Dehghani in 2019, the concept responds to the operational bottlenecks, coordination frictions, and scalability constraints faced by centralised data platforms in large, complex organisations [6], [21].

Rather than relying on a central data team to ingest, model, and provision data for the entire enterprise, Data Mesh advocates a distributed model where business domains are accountable for their own analytical data. This decentralisation aligns technical responsibilities with domain-specific knowledge, thereby fostering data quality, agility, and relevance [21], [22].

Data Mesh is anchored in four foundational principles:

- Domain-oriented decentralised data ownership and architecture,
- Data as a product,
- Self-serve data infrastructure as a platform,
- Federated computational governance.

Together, these principles shift the focus from centralised orchestration to federated collaboration. Domains become responsible not only for producing and consuming data, but also for maintaining its quality, documentation, and discoverability. This new organisational logic introduces roles such as Data Product Owners and Domain Data Stewards, which are embedded within business domains rather than concentrated in IT [21], [22].

Implementing Data Mesh entails more than architectural redesign. It requires significant organisational transformation, where success hinges not only on platforms and pipelines, but on how roles are defined, responsibilities embraced, and cross-domain collaboration institutionalised. The next section explores each principle in depth, focusing on their concrete implications for how data work is structured and governed across domains.

2.2 Data Mesh Principles and Their Organisational Implications

Each principle of Data Mesh not only restructures data architecture but also redefines how responsibilities are distributed across the organisation. This section examines their practical implications, focusing on the new roles they introduce, the behavioural shifts they require, and the support structures needed for successful adoption.

Domain-oriented decentralised ownership assigns accountability for analytical data to the business domains that generate and understand it. Instead of relying on centralised teams, each domain is responsible for producing, curating, and exposing its own data products. This transition draws on domain-driven design and aims to enhance scalability, responsiveness, and contextual relevance [6], [23].

However, this shift demands a fundamental change in how business teams perceive their role in data delivery. Traditionally viewed as consumers, they must now also act as producers, responsible not only for reporting but for the full data lifecycle. Two new roles are central to this transition:

- **Data Product Owner:** Is responsible for offering and governing the data products in its domain. They must ensure that the data products are interoperable and meet the requirements of the consumers [24].
- **Domain Data Steward:** Focuses on metadata management, access controls, and compliance. They act as custodians of data quality and standards within the domain.

These roles are expected to emerge within the business, not be imposed externally. Yet without dedicated support and reconfigured expectations, this can lead to confusion and friction [21].

Data as a product reframes data from being a passive by-product of operations into a value-generating asset with defined consumers, clear ownership, and lifecycle responsibilities. The DATSIS framework (Discoverable, Addressable, Trustworthy, Self-describing, Interoperable, Secure) provides a quality standard for what qualifies as a usable data product [6].

In practice, this principle implies that business domains must take responsibility for the completeness, clarity, and usability of the data they expose. However, this shift cannot be achieved through job titles alone: it must be integrated into incentive structures, resource planning, and performance evaluation [25]. Eichler et al. (2022) similarly warn that benefits often remain abstract, while accountabilities are immediate [26].

Moreover, the successful adoption of data product thinking depends on effective support structures. As Hasan and Legner (2023) argue, real organisational traction requires aligning new responsibilities with incentives and recognising the procedural and psychological load placed on business stakeholders [25].

Self-serve data infrastructure as a platform enables decentralised teams to build and manage their own data products independently. Maintained by a central platform team, this shared infrastructure provides accessible tooling, automation, and governance capabilities that abstract technical complexity [6], [7].

Organisationally, this demands a change in posture from central IT. Rather than acting as gatekeepers, they become enablers, offering reusable components, onboarding journeys, and documentation that lower the barrier to entry for business users. As observed in the Toyota case, low-code tooling was introduced specifically to make data modelling accessible to non-technical profiles.

Yet this enablement requires hybrid collaboration: domain teams require support to get started, while IT needs feedback to evolve the platform in a usable and scalable way [22].

Federated computational governance balances domain autonomy with enterprise-wide consistency. Governance responsibilities are distributed to the domains but coordinated through shared standards, automated policies, and collaborative forums [6], [27].

Practically, this means that organisations must invest in cross-functional governance councils, role-based policy frameworks, and iterative alignment mechanisms. Without these, federated governance can devolve into local improvisation or even hidden centralisation [7], [27].

In summary, the four principles of Data Mesh bring a fundamental shift not only in how data is architected, but in how work is distributed, how teams collaborate, and how responsibility is embedded within the business. Each principle ultimately relies on people adopting new roles, navigating new expectations, and engaging in unfamiliar forms of collaboration. These are human-centred shifts that require active enablement, cultural alignment, and sustained support. As such, change management and stakeholder onboarding should not be treated as peripheral concerns: they are core to the viability of Data Mesh itself.

2.3 Change Management in Data and Digital Transformation

As scholars in digital transformation consistently argue, technological innovation alone is insufficient. It must be accompanied by deliberate processes for stakeholder engagement, responsibility realignment, and organisational change [28], [29]. Change management has long been recognised as a critical success factor in large-scale IT and data initiatives, with common challenges including resistance to change, leadership misalignment, poor communication, and insufficient training [30].

These challenges are particularly significant in data transformations, where abstract concepts like "ownership," "governance," and "product thinking" can be difficult to internalise without dedicated support [31]. Data Mesh intensifies this by shifting accountability from centralised delivery models to domain-based ownership, asking business stakeholders to adopt unfamiliar roles such as Data Product Owner or Domain Data Steward, often without the necessary preparation. Eichler et al. (2022) found that data providers frequently face role ambiguity, lack of motivation, and unclear links between their efforts and organisational outcomes [26].

Psychological ownership is critical here: when individuals feel empowered and recognised, they are more likely to embrace new responsibilities. Conversely, imposed changes with unclear benefits often lead to disengagement or regression to prior habits [32]. This means that introducing new roles cannot rely on job titles or RACI charts alone: it requires clear communication, targeted training, role modelling, community support, and performance alignment.

Yet despite this, most studies on Data Mesh remain focused on architecture and infrastructure, with limited attention to change management. Exceptions include the case study of Saxo Bank by Joshi et al. (2021) [27], which highlights the governance challenges in a regulated setting, and Araújo Machado et al. (2021) [5], who call for further research on the human and organisational dynamics of adoption.

This lack of structured guidance on how to navigate stakeholder onboarding, role transition, and resistance represents a significant gap in the current literature. This thesis seeks to address that gap by applying a change management framework to the empirical case of Toyota Motor Europe. The goal is to understand how change was enacted in practice and to derive a generalisable framework that can support other organisations facing similar challenges.

2.4 Comparing Change Management Models (Lewin, ADKAR, Kotter)

Over the decades, the field of change management has evolved through foundational contributions that continue to shape both theory and practice. Among the most prominent models are Lewin's 3-Step Model, Kotter's 8-Step Process, and the ADKAR framework. These models are not mutually exclusive but reflect different lenses and levels of intervention in organisational change.

Understanding their nuances is crucial to selecting the framework best suited to the cultural and structural requirements of decentralised data transformation initiatives such as Data Mesh.

2.4.1 Lewin's 3-Step Model

Kurt Lewin's model is one of the earliest structured approaches to organisational change. Introduced in 1947, Lewin's process is comprised of three core stages:

- Unfreezing: destabilising the status quo and preparing the organisation for change.
- Changing: transitioning through uncertainty toward a new behavioural norm.
- Refreezing: stabilising and institutionalising the new behaviours.

The unfreezing phase requires organisations to critically examine existing structures, beliefs, and behaviours. It calls for a conscious dismantling of prior assumptions and a psychological unfreezing through awareness-raising, behaviour analysis, and anticipatory engagement with resistance [33], [34]. During this stage, Lewin emphasised the role of "field force analysis" (identifying and reducing restraining forces while amplifying driving forces) to motivate transition [35].

The change phase involves adopting new values, mindsets, and practices. It is often the most turbulent stage, marked by uncertainty and resistance. Here, leadership plays a key role in guiding employees through the ambiguity, offering support, resources, and reassurance as they abandon old habits and test new approaches [34].

In the final refreezing phase, the goal is to crystallise new behaviours into stable routines. This entails codifying change through policies, reward systems, and training so that the transformation becomes sustainable. However, there might not be enough time to re-stabilise before the next change cycle begins. Furthermore, the model has been criticised for its linearity and its limited attention to power dynamics, emotion, and communication in the change process [35], [31], [36].

Despite these critiques, Lewin's model retains value for its simplicity and foundational insight into behavioural change. It is particularly useful when changes are episodic and planned, as opposed to emergent or iterative.

2.4.2 Kotter's 8-Step Model

John Kotter extended Lewin's work by developing a detailed process for leading complex, organisation-wide transformations. Based on empirical observations and field research, Kotter's model introduces eight sequential steps [30]:

- Create a Sense of Urgency
- Build a Guiding Coalition
- Form a Strategic Vision and Initiatives
- Communicate the Vision
- Empower Broad-Based Actions
- Generate Short-Term Wins
- Sustain Acceleration
- Institute Change.

The model begins with creating urgency: a psychological and strategic pivot intended to disrupt complacency and spark commitment. Kotter warns that without this sense of urgency, change efforts are unlikely to succeed. Change leaders need to highlight market threats, inefficiencies, or strategic opportunities to overcome inertia and mobilise action [30].

Next, building a guiding coalition ensures the presence of influential advocates capable of driving the change forward. Once formed, this group is responsible for shaping and articulating a compelling vision that provides direction and meaning for all stakeholders [36]. Communication is not merely an announcement, it must be multi-directional, iterative, and integrated into daily operations.

Empowerment follows communication. This involves removing organisational obstacles, changing legacy systems that impede progress, and encouraging innovation. Kotter underlines the need for both structural changes and psychological safety to enable people to act without fear of retribution. The next steps, generating and celebrating short-term wins, are designed to build momentum and legitimacy. Without visible evidence of progress, scepticism can grow and reduce motivation [30].

Importantly, Kotter recognises the risk of premature celebration. His seventh step emphasises consolidation: embedding changes into broader systems and encouraging continued innovation. The final step, institutionalisation, ensures that new behaviours are reinforced through recruitment, training, performance evaluation, and leadership development.

While widely adopted, Kotter's model has been critiqued for being overly linear and hierarchical [36]. Nevertheless, the model's structured clarity and emphasis on leadership make it highly actionable, especially for complex, strategic transformations.

2.4.3 ADKAR

Unlike the previous models, ADKAR (Awareness, Desire, Knowledge, Ability, Reinforcement) is structured around individual change outcomes. Created by Jeff Hiatt, it reflects a bottom-up, outcome-oriented approach to managing the people side of change [36].

The model's strength lies in its sequencing of personal milestones. It begins with Awareness: informing individuals about the need for change and what is at stake. This stage is not only about communication but also about tailoring the message to different audiences based on their proximity to the change.

Next is Desire, which focuses on cultivating willingness. Without intrinsic motivation, awareness alone may not drive action. ADKAR thus considers emotional buy-in, personal impact, and perceived fairness of the change as key factors. This is followed by Knowledge, where individuals learn what is required to change: the tools, behaviours, and understandings necessary for success. Then comes Ability, the stage in which knowledge is translated into actual performance. Here, training, coaching, and time to practice are critical [33]. Finally, Reinforcement ensures the sustainability of change through feedback loops, recognition, and ongoing support.

ADKAR's focus on individual progress makes it particularly useful in large-scale transformations where each employee's journey may be unique. However, it lacks explicit guidance for strategic alignment, coalition-building, or cross-functional coordination, elements essential for complex transformations like Data Mesh. Furthermore, in hierarchical settings, senior management typically retains power over decisions, limiting the scope for grassroots-led change even when individual adoption is high [36].

2.4.4 Framework Comparison

While all three models offer valuable perspectives, they differ significantly in their underlying assumptions and level of abstraction. Lewin's model is foundational and offers a clear, linear progression for managing behavioural change, but its simplicity and static assumptions limit its utility in dynamic and decentralised contexts. ADKAR, on the other hand, excels at addressing individual change readiness, making it a strong tool for diagnosing resistance and supporting targeted interventions. However, its individual-centric focus provides limited guidance on collective coordination, leadership dynamics, or system-wide mobilisation, elements that are essential for implementing Data Mesh across business and IT domains.

Kotter's model stands out by bridging these levels: it offers a structured yet adaptable roadmap that incorporates urgency, stakeholder alignment, cultural anchoring, and behavioural reinforcement. Unlike Lewin, it provides tactical granularity; unlike ADKAR, it engages organisational structures and coalitions. For a transformation as complex and layered as Data Mesh, Kotter's framework offers the most comprehensive foundation.

For these reasons, this thesis uses Kotter's 8-Step Process as a diagnostic framework for analysing Data Mesh implementation at Toyota Motor Europe. The model offers a structured entry point to investigate how organisations generate alignment, enable action, and embed new responsibilities. However, it was designed for top-down, sequential transformations. Its assumptions about authority and linearity may not fully align with federated settings, where change is distributed, iterative, and co-constructed across semi-autonomous domains.

Recognising this, the following section justifies the selection of Kotter while outlining the interpretive flexibility applied throughout the analysis. Rather than using the model prescriptively, this thesis adapts it to the realities of decentralised change.

2.5 Justifying Kotter for Data Mesh Transformations

Kotter's 8-Step Process has been widely adopted in practice-oriented change literature since its formalisation in *Leading Change* (1996). It frames transformation as a staged journey that begins with urgency and culminates in institutionalised change. The model is particularly valuable in technology-led transformations, where clear visioning, cross-functional coordination, and cultural reinforcement are critical to success [37], [30].

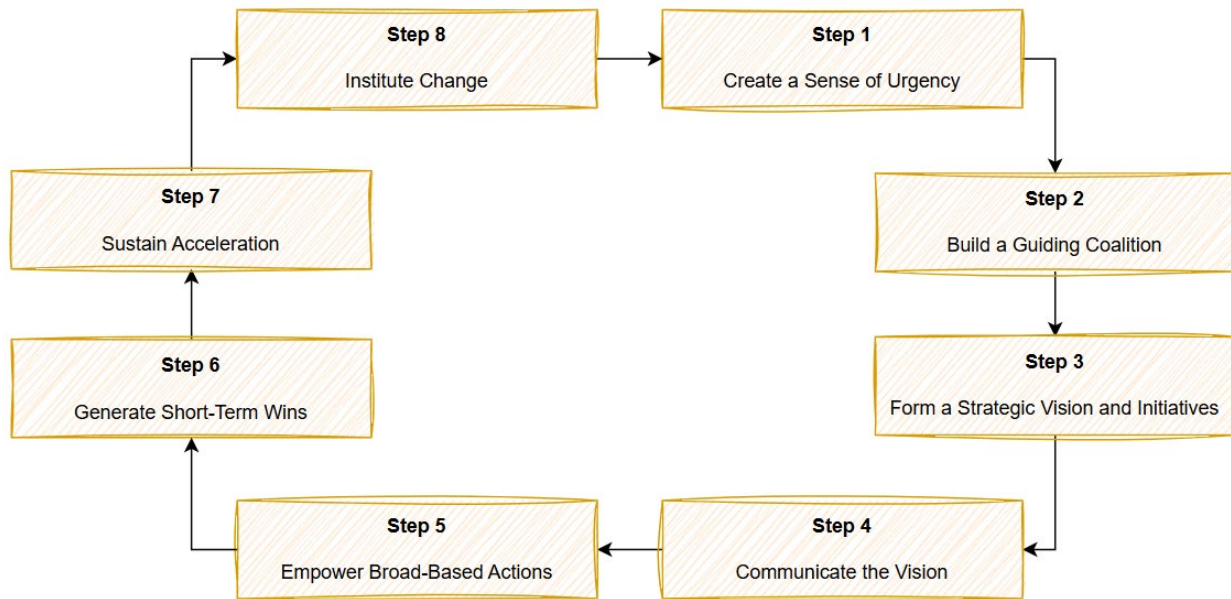


Figure 1 – Kotter's 8-Step Model

What makes Kotter's framework particularly relevant to Data Mesh is its holistic approach to change. Unlike models that focus only on communication plans or training programmes, Kotter's model integrates emotional, political, and structural elements of transformation. It begins with the recognition that large-scale change requires emotional buy-in and urgency, not just rational arguments. In the context of Data Mesh, this aligns with the need to communicate the limitations of centralised data architectures, highlight the cost of inaction, and frame the new roles and responsibilities (such as data product ownership) as both necessary and empowering [16]. Many organisations fail at this first hurdle, assuming that a PowerPoint presentation or executive memo will suffice to overcome years of well-established practices.

The model's emphasis on a guiding coalition is also crucial. Implementing Data Mesh requires coordination between central platform teams, data governance leads and domain managers. These groups must act not only as planners but as advocates and role models, reinforcing the vision and removing institutional obstacles. In many organisations, however, responsibility for Data Mesh is diffused across fragmented teams, leading to a lack of coherence and accountability. Kotter's insistence on a cross-functional, empowered coalition is a direct response to this challenge [30], [27].

Kotter's third step, form a strategic vision and initiatives, has a direct analogue in the Data Mesh principle of "data as a product." Organisations need to clearly articulate what success looks like,

how roles will evolve, and what capabilities will be built. Without a coherent vision for what a domain's responsibility entails and how data products should be managed, many teams resort to ad hoc practices or passive resistance. The literature repeatedly shows that the absence of a shared language and vision is a major obstacle to adopting decentralised data ownership [26].

Subsequent steps in Kotter's model deal with operational execution. Building a guiding coalition and enabling action by removing barriers correspond directly to the need for early adopters in domain teams: people willing to experiment with data product roles, provide feedback, and help spread practices horizontally. In the Saxo Bank case, for example, success in federated governance was made possible by identifying influential local actors and giving them a voice in governance formulation and rollout [27]. The removal of barriers, whether they are legacy processes, unclear role definitions, or insufficient tooling, is equally essential and resonates with the emphasis in the Data Mesh literature on platform self-service and capability enablement [6].

Generating short-term wins is another step that is often overlooked in Data Mesh transformations. Many organisations focus on building platform infrastructure or crafting governance policies without delivering tangible business value in the near term. Kotter's model emphasises the need to demonstrate early success, celebrate small victories, and use them to build momentum.

The final steps, sustain acceleration and institute change, relate to the institutionalisation of new behaviours and structures. For Data Mesh, this includes integrating data product ownership into job descriptions, aligning performance incentives with product outcomes, and embedding governance practices into everyday workflows. Otherwise, old habits reassert themselves, and the transformation might stop.

While Kotter's model offers a compelling blueprint for Data Mesh adoption, it is not without limitations. Critics argue that the model assumes a linearity and stability that may not hold in dynamic or iterative environments. Agile transformations, for instance, often require recursive adaptation rather than straightforward execution. However, this critique does not invalidate the relevance of the model; rather, it suggests that its application to Data Mesh must be adaptive, not prescriptive. The steps may unfold in parallel, some may be revisited, and the process must be constantly renegotiated in response to organisational dynamics.

Despite these limitations, the model's strength lies in its clarity, communicability, and integration of cultural and structural dimensions of change. It offers a language and sequence through which organisations can coordinate effort, build consensus, and measure progress. Given the

organisational ambiguity and novelty of Data Mesh, such a framework is particularly valuable. This thesis thus applies Kotter's 8-Step Model as a deductive lens to interpret empirical findings from Toyota Motor Europe and to inform the development of a tailored framework for Data Mesh change enablement.

2.6 Identifying the Research Gap

The preceding sections have outlined a growing consensus across both academic and practitioner literature that traditional centralised data architectures are increasingly inadequate for supporting enterprise-wide scaling, agile methods, and business-aligned analytics. In this context, the emergence of Data Mesh as a decentralised, domain-driven, product-oriented model represents a significant and timely shift [5]. Through its emphasis on domain ownership, data-as-a-product, self-serve platforms, and federated governance, Data Mesh addresses critical challenges in scalability, interoperability, and local relevance of data [16].

However, while the theoretical promise of Data Mesh is increasingly well articulated, its implementation realities remain poorly understood, especially in academic literature. The available research has largely concentrated on the technical and architectural dimensions of Data Mesh: defining its principles, contrasting it with other paradigms, and proposing reference models for infrastructure and metadata [38], [39]. Only a handful of studies have begun to address the organisational implications, and even fewer provide empirical insight into how organisations actually implement Data Mesh in practice [24], [40].

Among the few notable exceptions, Joshi et al. (2021) provides a detailed case of Saxo Bank's implementation, focusing primarily on governance mechanisms [27]. Eichler et al. (2022) examine the challenges faced by data providers in enterprise marketplaces, indirectly shedding light on some of the cultural and incentive issues associated with role changes [26]. Hasan and Legner (2023) adopt work system theory to analyse the institutional dynamics of data product implementation, revealing the organisational friction involved in shifting to product-oriented data delivery [25]. Despite their contributions, none of these studies provide a comprehensive framework for managing the human side of the transformation.

Most importantly, there is a complete absence of literature that explicitly applies structured change management models, such as Kotter's 8-Step Process, to the Data Mesh transformation. This is a striking omission, given that Data Mesh involves a profound redistribution of data ownership, decision-making, and responsibility. Business stakeholders, used to passive data consumption, are

now expected to become data producers, stewards, and owners. Central IT and data teams must transition from gatekeepers to enablers. Governance must move from top-down control to distributed coordination. These shifts require deliberate efforts to manage change: to align incentives, communicate vision, develop skills, overcome resistance, and institutionalise new practices [37].

Moreover, a big part of the practitioner literature surrounding Data Mesh is based on vendor white papers, conference talks, and blogs [6], [10], [41]. While informative, these sources often emphasise success stories and technical innovations, underplaying the social and organisational obstacles encountered during implementation. As a result, there is limited empirical understanding of the barriers, enablers, and failure modes in Data Mesh transformations.

This thesis addresses this critical research gap by integrating change management theory, specifically Kotter's 8-Step Model, with a detailed case study of Toyota Motor Europe's Data Mesh implementation. By doing so, it aims to contribute three novel elements to the academic and practitioner discourse:

First, it offers an empirically grounded analysis of how Data Mesh implementation unfolds in a large enterprise, with attention to the onboarding of business roles such as Data Product Owner and Domain Data Steward. Second, it operationalises Kotter's change model within the context of Data Mesh, identifying how each step manifests in practice. Finally, it introduces a generalisable change enablement framework tailored to organisations pursuing Data Mesh adoption, adapting Kotter's model to meet the specific demands of this transformation.

In sum, this work seeks to elevate the discourse around Data Mesh from one focused primarily on architectural potential to one grounded in organisational reality, empirical rigor, and actionable insight.

3 Research Methodology

3.1 Research Design

This study adopts a qualitative, abductive case study methodology to explore how organisations can effectively onboard business stakeholders into new roles during a Data Mesh implementation. The research is grounded in the recognition that Data Mesh is not only a technical or architectural innovation, but also a profound organisational transformation that reshapes roles, responsibilities, and power dynamics across IT and business lines.

A qualitative approach is well-suited to examining such complex, socially embedded phenomena. It enables deep engagement with participant perspectives and allows the researcher to trace how meanings, interpretations, and actions evolve over time. Since the study seeks to answer “how” change occurs within organisations, especially how roles like Data Product Owner and Domain Data Steward are understood, resisted, or embraced, qualitative inquiry is appropriate [42].

The study follows an abductive reasoning, a methodology that iterates between theory and empirical data to refine conceptual understanding. Abduction is especially suitable in domains where theory is incomplete or underdeveloped, as it allows for the refinement of conceptual frameworks through engagement with real world experience. Rather than applying theory deductively or generating it purely inductively, abduction allows the researcher to engage in a dialogic process between empirical observation and conceptual framing [43].

To operationalise this reasoning, the study uses a single-case design. The case of Toyota Motor Europe (TME) was chosen for its information-rich nature, as the company is currently engaged in a Data Mesh transformation involving multiple domains and stakeholder groups. Rather than aiming for statistical generalisation, the goal is to derive insights from this case that may inform theory and guide practice in similar organisational contexts.

In line with Yin’s (2018) principles for case study research, this study clearly defines its unit of analysis: the onboarding process of business domain stakeholders into new data roles as part of the broader Data Mesh implementation. The case was selected not to evaluate the overall success of the Data Mesh journey, but to examine how change unfolds at the intersection of role enablement, governance, and domain ownership, especially in environments where decentralised responsibilities challenge established norms.

3.2 Data Collection

The primary empirical material was collected through semi-structured interviews conducted with stakeholders involved in the Data Mesh implementation at Toyota Motor Europe [43]. Interviews were chosen as the main data collection technique because they offer the flexibility to explore complex phenomena while allowing participants to express their experiences and perceptions in their own terms [42].

A purposive sampling strategy was used to ensure diversity across functional roles, levels of involvement, and perspectives on the transformation. Participants were selected in coordination with a senior manager at TME who had broad visibility over the Data Mesh initiative. This helped identify stakeholders from business domains, platform teams, data governance, and change management, with direct exposure to the onboarding or enablement of new data roles.

The sample includes 16 interviews, conducted over ten working days. Each session lasted between 25 and 60 minutes, depending on the participant's role and availability. Interviews were held in English or French, based on the participant's preference. When conducted in French, a professional translation software was used: questions and answers were translated using DeepL, with manual correction to preserve nuance and accuracy.

Interviewees included:

- Business representatives assuming roles such as Data Product Owner or Domain Data Steward
- Platform and architecture team members involved in self-serve infrastructure development
- Governance leads and members of the Data Mesh team responsible for policy setting and coordination
- Embedded hybrid roles that sat between business and technology functions

Each interview followed a semi-structured guide, which evolved over time as patterns emerged (Appendix 1 – Interview Guide). Topics included participants' background, role clarity and onboarding, change process and support, as well as cultural and organisational dynamics. This allowed for consistency across interviews while also leaving room for participants to introduce novel themes [44].

All interviews were either recorded and transcribed through Microsoft Teams or recorded with a smartphone and transcribed with the internal tool of Microsoft Word. The transcripts were then cleaned manually and anonymised to preserve confidentiality. In addition to interviews, the research drew on internal documentation, such as role descriptions, governance models, onboarding templates, project charters, and blog posts. These documents were used to triangulate findings and provide context to stakeholder perspectives.

Beyond formal interviews, informal conversations, field notes from project meetings, and spontaneous reflections from embedded observations were used to support analytical depth. This insider access, afforded by the researcher's internship, provided contextual richness while also requiring conscious separation between operational engagement and research interpretation.

To reduce researcher bias and improve reliability, interviews were triangulated with internal documents, and coding was conducted manually with reflective memos to ensure consistency and transparency.

The table below summarises the key characteristics of the interviews.

Table 1 – Interviews characteristics

Interview Code	Length of interview	Stakeholder category
A	25'55	Tech/Platform
B	48'15	Governance & Change
C	46'09	Tech/Platform
D	37'40	Business Domain
E	43'59	Business-Facing Tech
F	59'38	Business Domain
G	34'33	Business-Facing Tech
H	27'40	Tech/Platform
I	58'45	Tech/Platform
J	37'50	Business Domain
K	40'58	Governance & Change
L	47'27	Business Domain
M	53'59	Business Domain
N	34'40	Governance & Change
O	59'39	Business Domain
P	31'59	Governance & Change

Together, these sources provide a multi-faceted empirical base, enabling a robust understanding of how Data Mesh is perceived, enacted, and supported across organisational boundaries.

3.3 Data Analysis

3.3.1 Abductive Reasoning and Thematic Coding

Data analysis followed the logic of abductive reasoning, which entails a continuous back-and-forth movement between theoretical concepts and empirical observations [43]. The aim was not to test a predefined hypothesis but to generate new theoretical insights grounded in the data.

Thematic analysis was employed to identify patterns, concepts, and relationships within the interview transcripts. A combined deductive–inductive coding strategy was used. Deductive codes were derived from John Kotter’s 8-Step Change Model [13], which served as the initial theoretical lens. These codes included categories such as “Create a Sense of Urgency,” “Build a Guiding Coalition,” “Communicate the Vision,” and “Empower Broad-Based Action.” At the same time, inductive codes were generated through open coding, allowing new themes to emerge directly from the data, such as “Tensions in Ownership,” “Business-IT Divide,” and “Complexity of Data Products.”

Coding was performed manually and iteratively. Each transcript was read multiple times, and memo-writing was used to capture reflections, patterns, and potential analytical leads. The process led to the identification of both confirmatory and novel themes, which informed the development of a new, adapted change management framework for Data Mesh implementation. An excerpt of the result of the coding can be found in Appendix 2 – Extracts from Interviews.

3.3.2 Triangulation

In addition to interviews, supplementary data sources such as internal documentation and informal discussions were used to triangulate findings and support contextual understanding. While triangulation was not a central focus of the analysis, it served to validate key patterns and ensure coherence between sources.

Together, these analytical strategies ensured that both thematic insights and contextual nuances were captured with sufficient depth and consistency.

3.4 Research Quality

To ensure methodological rigor, this research adopts the trustworthiness criteria proposed by Lincoln and Guba [45]: credibility, transferability, dependability, and confirmability.

Credibility was reinforced through purposive sampling, iterative coding, and the use of a well-established theoretical framework. The interviewees were selected after discussion with a Senior Manager with several years of experience at Toyota and in the IT & Digital division. This helped to choose people with different but complementary views on this implementation.

At the same time, the dual role of the researcher as both an intern and a data collector created unique access to informal insights, but also posed potential risks of bias in interpretation. While familiarity enabled richer contextual understanding, it may also have subtly shaped expectations or interpretations of stakeholder responses. To mitigate this, all quotes were interpreted considering their context, and analytical memos were used to critically reflect on assumptions during coding.

Transferability was supported by detailed descriptions of the organisational context, allowing readers to assess relevance to similar settings. The description of the context of Toyota can be found in the next sub part 4.1 Organisational and Data Context.

Dependability and confirmability were addressed by documenting coding decisions, reflecting critically on researcher positionality, and maintaining consistency in the analytical process. An excerpt of the extract from the interviews and the coding associated to it can be found in Appendix 2 – Extracts from Interviews.

The findings have been presented to a panel of professionals at TME for validation. The sentiment extracted from the interviews have been validated by these professionals, as well as the development of the new framework.

4 Empirical Findings: Data Mesh Implementation at Toyota Motor Europe

4.1 Organisational and Data Context

The analysis presented in this chapter reflects the state of Toyota Motor Europe's Data Mesh transformation as observed during the research period. Importantly, this initiative is ongoing and constantly evolving. Several of the challenges discussed here have already been acknowledged by the transformation team, and steps are being taken to address them. Moreover, the transformation journey began more than two years ago, and many interviewees were involved in projects with significant regulatory or time constraints that accelerated onboarding beyond ideal timelines. The goal of this thesis is not to pass judgment but to offer constructive insights that may support and inform continued progress.

Toyota Motor Europe (TME) is the regional headquarters of Toyota Motor Corporation for operations across Europe. It oversees the manufacturing, sales, marketing, and after-sales service for Toyota, GAZOO Racing (GR) and Lexus vehicles across more than 50 countries. With thousands of employees across manufacturing plants, sales offices, R&D centres, and logistics hubs, TME is a complex, multi-layered organisation with both centralised corporate functions and locally autonomous units. This structure poses unique challenges and opportunities for digital transformation and data-driven initiatives, including the implementation of a decentralised data architecture such as Data Mesh.

Historically, TME relied on a centralised data delivery model, typical of many large industrial organisations. Data extraction, transformation, storage, and analytics were managed by a central data and analytics team. Business units such as marketing, supply chain, and after-sales were positioned as data consumers. The central team built and maintained data flows, managed business intelligence dashboards, and acted as the organisation's single point of access to data. Although this model enabled standardisation and control, it faced significant limitations as data volume, diversity, and demand grew.

Interviewees at Toyota Motor Europe highlighted several structural and organisational limitations associated with the previous centralised data model. Initially, data analytics responsibilities were concentrated in what one stakeholder referred to as a "Business Intelligence Competency Centre", with no centralised advanced analytics function in place at the time (Interview A). As they began to

“have more needs for data than [they] had before”, this centralised model quickly became outdated (Interview E).

A further limitation was the absence of centralised accessibility. Data was frequently stored locally, and retrieving it required informal processes: “You need to find the right person and ask him to share it” (Interview K). This reliance on interpersonal networks, rather than structured access mechanisms, not only hindered operational efficiency but also contributed to inconsistencies in data use across teams.

In addition, TME faced increasing pressure from global corporate leadership and industry regulation to improve data quality, traceability, and agility—particularly in the context of sustainability reporting, real-time supply chain optimisation, and personalised customer experiences. These requirements could not be met with a monolithic, centralised data platform.

Governance gaps further exacerbated this fragmentation. “If you don't have a proper governance in place,” one interviewee explained, “the data is all over the place and you do not understand the value of the data itself” (Interview A).

From an organisational perspective, these conditions encouraged siloed development. “Before, people were working in silos, doing their own solution for their team, not realising that there are so many things that can be replicated,” one stakeholder remarked (Interview B). This led to duplicated effort, inconsistent reporting logic, and a proliferation of unverified data assets—symptoms of structural misalignment rather than individual oversight.

In response to these challenges, TME initiated a Data Mesh transformation in 2023, led jointly by its Digital and Data Strategy Office and the Central IT function. The transformation aimed to restructure the data operating model, decentralise ownership, and enable business domains to develop and manage their own data products. The overarching goal was to scale the delivery of analytical and operational data without compromising on quality, security, or interoperability.

The first phase of implementation targeted a small number of pilot domains selected based on their data maturity, operational criticality, and leadership buy-in. Each pilot domain was tasked with identifying key data assets, defining data product use cases, and nominating stakeholders to take on new roles such as Data Product Owner and Domain Data Steward. At the same time, the central team began developing a self-serve data platform, including automated cataloguing, lineage tracking, role-based access control, and reusable transformation pipelines.

Importantly, the transformation was positioned not as a technical migration but as an organisational change initiative, requiring collaboration across IT, governance, and business lines. Multiple workstreams were launched to address platform development, role definition, governance model design, and cultural enablement. Early efforts were made to communicate the purpose of the transformation, build alignment, and pilot new ways of working.

This empirical setting—an industrial, distributed organisation undergoing a structured yet still maturing Data Mesh transformation—provides an ideal context to explore the challenges of role onboarding, stakeholder alignment, and organisational change.

4.2 Mapping Empirical Findings to Kotter’s 8-Step

The implementation of Data Mesh at Toyota Motor Europe provides a valuable empirical lens through which to analyse the organisational transformation associated with decentralising data responsibility. To systematically examine this change process, empirical insights from stakeholder interviews were coded against Kotter’s 8-Step to Change model for leading organisational change. The following subsections present a step-by-step mapping of those findings.

4.2.1 Step 1: Create a Sense of Urgency

Kotter’s first step is foundational for any transformation initiative. Without a shared recognition that the status quo is not sufficient anymore, organisational momentum stops. At Toyota Motor Europe, the urgency for change was strongly felt within IT and central data teams, but less consistently internalised across business domains.

Several interviewees emphasised growing dissatisfaction with the limitations of the centralised data model. Some stakeholders mentioned having long observed the duplication of effort and the inability to scale analytics. “Avoid duplicate copies of data at several places,” one participant stated, summarising a recurrent issue caused by a lack of centralised standards and visibility (Interview A). Another explained, “We have more needs for data than we had before,” suggesting that analytical demand was outpacing the responsiveness of the existing model (Interview E).

Yet, this dissatisfaction was not always transformed into collective urgency. Some domain stakeholders acknowledged inefficiencies but did not see themselves as active participants in solving them.

In summary, the conditions for urgency were present at Toyota (e.g., central backlog, local inefficiencies), but the emotional ownership of that urgency was uneven. For a transformation like Data Mesh to succeed, technical rationale must be accompanied by contextualised, domain-relevant narratives that help business stakeholders see both the risk of inaction and their role in addressing it.

4.2.2 Step 2: Build a Guiding Coalition

In Kotter's model, the guiding coalition is the driving force of transformation: a committed group with sufficient authority, expertise, and credibility to steer change. Kotter distinguishes between two key roles. The first are change leaders, typically senior figures positioned high in the organisation, who shape the strategic vision and possess the power to prevent resistance from derailing progress. Their credibility ensures that initiatives are respected and followed. The second are change managers (functional specialists and mid-level leaders) who operationalise the transformation within units and functions.

At Toyota Motor Europe (TME), efforts to build such a coalition are evident. The Data Mesh Board includes senior leaders from Data Operations, Enterprise Architecture, Data Analytics, and Data Governance—illustrating the presence of high-level change leaders. Meanwhile, emerging hybrid roles such as Domain Data Stewards and Data Product Owners reflect attempts to embed data responsibility within domains and promote local engagement with the transformation. While these roles are not designed primarily as change managers, they serve as operational anchors for the decentralised model and can play a key role in sustaining change at the domain level.

The construction of this coalition has been strongly supported by top-down leadership, which aligns closely with Kotter's emphasis on visible sponsorship and strategic direction. When business engagement has been insufficient, senior management has stepped in to reinforce commitment: "Where we do not get enough buy-in from the business, we get the support of our management that go and talk with the business management" (Interview A). This reflects a proactive leadership posture, helping to establish early momentum and legitimacy for the initiative, even if full local ownership is still developing.

While the strategic backbone is solid, operational coordination has remained ad hoc and variable across domains. One interviewee explained, "We did get a lot of guidance and a lot of support. They pulled in other people with different competencies" (Interview E). This support was appreciated, but the broader coalition lacks consistent ownership in the business. As another respondent observed, "Somebody needs to take the lead in organising this and say: 'this is where we

are going to, and these are the next steps.’ And that for me is an IT role, not a business role in this kind of project” (Interview D). This perception reinforces a problematic pattern: IT remains the de facto driver, while business roles are often reactive or peripheral in shaping the transformation.

At the same time, several interviewees emphasised the importance of hybrid profiles to bridge the gap between technical depth and business relevance. One participant noted, “We need more hybrid profiles that understand both the business and the data” (Interview G). Another advocated for the creation of ‘Data Citizens’, professionals with domain knowledge who are also empowered to participate in data modelling and governance: “Move towards a Data Citizen, a profile more hybrid and more engaged with the data lifecycle” (Interview G). These emerging roles align closely with the concept of middle-layer change managers in Kotter’s model, which highlights the importance of embedded local champions who can translate strategic goals into operational traction [30].

Structurally, TME has invested in coordination mechanisms, such as a data governance council, a steering board, internal communities, and shared communication channels (Interview P). These initiatives mark a clear step forward in fostering alignment and transparency across functions. They have created spaces where domain actors, governance leads, and platform teams can interact more regularly. While these mechanisms do not yet amount to a fully integrated, empowered coalition with distributed leadership, they signal a growing institutional effort to formalise collaboration and create continuity across the transformation. The foundation for a cross-functional guiding coalition is emerging and continues to mature.

Interestingly, the Data Mesh team itself has taken a notable step by integrating a dedicated communication specialist into its transformation efforts. As one interviewee explained, “We are the only team that has its dedicated communication specialist,” while acknowledging that “we don’t have the habit to really onboard communication specialists for IT transformation” (Interview B). This move reflects an emerging awareness that communication is not merely a support function, but a strategic enabler of cultural alignment, stakeholder engagement, and sustained momentum, especially in complex, cross-domain transformations like Data Mesh.

Overall, the guiding coalition at TME demonstrates a promising combination of executive sponsorship, structural coordination, and growing hybrid participation. While Kotter’s model emphasises the importance of a unified, cross-functional coalition, the TME case suggests that decentralised transformations like Data Mesh may benefit from a layered coalition structure. This structure appears to operate at two levels: a strategic layer, where senior leaders provide legitimacy and direction, and an operational layer, where domain-level actors such as Data Product Owners

and Stewards drive local adoption and change. Although not fully institutionalised, this dual-level configuration may reflect an adaptive response to the distributed nature of Data Mesh.

4.2.3 Step 3: Form a Strategic Vision and Initiatives

Kotter's third step highlights the role of a clearly defined strategic vision in mobilising change. Rather than focusing solely on short-term objectives, such a vision reorients the organisation by challenging existing assumptions and projecting a coherent future state. As Appelbaum et al. observe, "An effective vision is essential in breaking the status quo and looking beyond the immediate goals of the organisation," providing employees with a frame of reference that helps them act decisively, even when initial steps are uncomfortable [30].

In the context of Data Mesh, this vision must do more than describe an architectural shift, it must create alignment across functions, clarify the roles of both technical and business stakeholders, and outline the intended outcomes in a way that feels tangible and actionable. It is not merely about systems; it is about meaning, motivation, and execution. At Toyota Motor Europe, the strategic vision for Data Mesh was clearly articulated at the leadership level. The transformation was framed as a step toward building a sustainable, federated data infrastructure that would enable the organisation to scale its analytics capabilities across domains. "You're going to contribute to the long-term strategy because these data products will be used by anybody in the organisation," one interviewee explained, underscoring that the vision extended beyond short-term use cases to foundational data assets with enterprise-wide impact (Interview C).

This strategic framing was supported by a focus on key principles such as data reusability, quality, and ownership. "The end goal is to have proper quality, governance and ownership of the data," noted one respondent (Interview A), while another emphasised the need to "create data products that are reusable" (Interview E). These messages align closely with the core principles of Data Mesh and suggest that the vision was not limited to technical modernisation but was intended to foster a more robust data culture across the business.

Importantly, the strategic vision was also connected to operational relevance. "A data product is something touching the reality," one interviewee explained, "we understand the immediate need and how we can consume, be part of it" (Interview K). This comment reflects an effort to link high-level objectives to day-to-day business needs, an important step in ensuring that the vision is understood and adopted beyond the IT and data strategy teams.

However, the vision alone is not enough. Paper et al. [46] warns that while people may understand a process on paper, “execution is the real difference between success and failure.” For the vision to become transformative, it must shape behaviours, expectations, and role definitions across the organisation. “Emphasise the importance of taking the ownership of the data, especially from the business side,” one interviewee urged (Interview L). This points to a critical insight: the vision cannot remain at the strategic or IT level, it must be embedded in the organisation and shift how people see their responsibilities.

In summary, TME’s Data Mesh vision successfully establishes a long-term direction focused on reusable data products, cross-organisational value, and federated ownership. It resonates with both architectural and cultural dimensions of change. Yet, while this vision is well-formed and clearly communicated at the leadership level, its practical translation into daily behaviour, particularly for business stakeholders unaccustomed to data responsibility, remains a work in progress. To move from aspiration to execution, the next challenge lies in communicating this vision consistently, tailoring it to each audience, and ensuring it becomes a shared driver of action across the organisation.

4.2.4 Step 4: Communicate the Vision

Kotter’s fourth step emphasises the need to communicate the strategic vision clearly, consistently, and tailored to different stakeholders. Effective communication is not just about transmitting information: it is about building understanding, alignment, and emotional engagement across the organisation.

At Toyota Motor Europe, communication of the Data Mesh vision took multiple forms, from onboarding sessions and internal communities to informal discussions and live demos. “We communicate through our communities, our events, and onboarding sessions as well,” one stakeholder explained. These efforts were supported by initiatives like data targeted role-based sessions (Interviewee A). Still, many interviewees acknowledged that “onboarding is the hardest part” and that communication must be continuous: “Repeating it once is never enough” (Interviewee P). Another added, “Always explain it like it would be the first time somebody has ever listened to it” (Interview B). This comfort Kotter’s in his saying that “ideas sink in deeply only after they have been heard many times” [47].

A major challenge was the need to adapt the message to different audiences. “We need explanation for VP level, executives, but also for beginners, for businesspeople, for data scientists, etc.,” one

participant noted. “They don’t need to know the technical details... just that their contribution adds value and that there is a positive outcome” (Interview B). In response, some transformation leads positioned themselves as internal translators: “I take very complex narratives or technical stories and try to translate them into more actionable, digestible narratives that can be understood by the business and also implemented by teams” (Interview B).

Despite these efforts, many business stakeholders reported difficulty understanding what was expected of them. “We presented the concept of data product, governance, roles, etc., but it lands pretty difficult as the explanations are still pretty technical” (Interview F). Another participant noted, “Everybody understood the concept, but they couldn't find the immediate steps to start with” (Interview K). This points to a gap not in the vision itself, but in its practical translation into first actions.

Moreover, the emotional dimension of communication emerged as critical. Several participants stressed the importance of generating excitement and reducing fear. “Take people by the hand and onboard them bit by bit. Be patient somehow, especially for the first time,” one advised (Interview J). Others noted that Data Mesh had to be “marketed like an employee event, not like IT,” using testimonials, success stories, and relatable examples to drive engagement (Interview B). The idea was not only to inform, but to motivate and demystify.

At the same time, communication efforts sometimes backfired when documentation was too technical, rigid, or premature. “While I appreciate the documentation,” one stakeholder explained, “they hand it over saying: ‘You need to prepare all of this before you can start talking to us’” (Interview G). This created frustration, as teams felt overwhelmed by expectations and not supported in execution.

In summary, Toyota’s experience illustrates the tension between top-down messaging and bottom-up absorption. While communication mechanisms were put in place, the diversity of audiences, the abstract nature of the vision, and the learning-by-doing nature of the transformation meant that alignment remained a moving target. Kotter’s model calls for vision communication that is not only frequent and multimodal, but also adaptive to context, respectful of capability, and supportive of incremental understanding. At TME, communication was active and well-intentioned, but its effectiveness varied depending on how well it translated into actionable insight and emotional clarity for each audience.

4.2.5 Step 5: Empower Broad-Based Action

Kotter's fifth step emphasises the need to remove obstacles that prevent individuals from enacting the change vision. Communication, while essential, is never sufficient on its own as explained by Kotter: Employees often need help in getting rid of obstacles to the change vision. Empowerment, as he later clarifies, typically involves addressing four major obstacles: structures, skills, systems, and supervisors. It is both a technical and psychological endeavour: requiring not only tools and training but also role clarity, emotional support, and trust in local initiative [30].

In the context of Data Mesh, empowerment means enabling domain teams to confidently own and deliver data products. At TME, several initiatives were introduced to support business domains in assuming new responsibilities. These included onboarding sessions, access to documentation, no/low-code tools, and peer support. One stakeholder explained, "The tools we selected are no/low code so business profiles can use it without any technical knowledge" (Interview B). Another recalled their onboarding experience: "Someone showed me and then I just continued... There is some documentation and colleagues helped me understand" (Interview C). This reflects an ecosystem where learning is partly structured, partly social.

Training was also central. "We offer upskilling trainings," one transformation lead explained, "and events help people get upskilling on their knowledge, but also understand how other teams are using Data Mesh" (Interview P). This cross-domain exposure helped mitigate information silos, critical in federated environments where local practices need to be harmonised. As Kotter emphasises, training plays a pivotal role in the empowerment process, and there is strong empirical support for its transformative impact.

However, empowerment at TME was not purely a matter of tools and training. It also required psychological support and guidance. "We are handholding, taking care of the psychological aspect," one IT lead explained. Another noted, "You do need a fair amount of guidance... I think what you really need is some IT people who take you by the hand and help you go through it" (Interview D). These comments reflect that while self-service is a stated goal, the reality still involves a dependency on central support—a transitional state in many Data Mesh journeys.

Workload clarity and time commitment were also addressed through role-based guidelines. "We summarise per role who is doing what with regards to the data product creation," one respondent said. "We give them estimations per role, how much time it would take depending on the T-shirt size of the data product" (Interview O). These practices help demystify expectations and reduce the

cognitive load of adoption, particularly for business users unfamiliar with agile or product delivery models.

Still, role ambiguity persisted. “We are saying: ‘You are the data product owner,’ and they reply: ‘No, I just want to report,’” one transformation leads recounted (Interview F). This highlights a cultural barrier: business users often did not perceive data ownership as part of their role, and resisted the accountability associated with it. Moreover, some teams encountered confusion about the division of labour. “Sometimes you do things just because someone needs to do it, not looking at who would be the right person to do it.” (Interview N). This illustrates that ownership was being formalised, but not yet normalised.

In response, IT teams often took a proactive stance, guiding the business through product design. “We [IT] took the lead to take the business along and say: ‘OK, this is the proposition I have to enrich the data, do you agree on this approach or not?’” (Interview E). This demonstrates a collaborative posture, but also underscores the continued centrality of IT in enabling execution.

Finally, some empowerment strategies reflected a more federated approach. “Some initiatives come from the entities,” one participant noted, “and then we use the concept of Yokoten—we set the same standard for other entities, which is then kind of bottom-up” (Interview K). This shows that local innovations were being diffused horizontally, creating a decentralised feedback loop consistent with Data Mesh principles.

In summary, Toyota made visible efforts to empower broad-based action: tools were simplified, training was offered, and documentation was made available. While not all teams experienced empowerment in the same way, these initiatives significantly lowered technical and structural barriers and laid the groundwork for a more autonomous model of data ownership. As Kotter emphasises, true empowerment requires removing fear, clarifying expectations, and building both skill and will. At TME, this process is well underway: part enablement, part cultural evolution. With continued investment in clarity, support, and confidence-building, the foundations are in place for broader and more sustained ownership across domains.

4.2.6 Step 6: Generate Short-Term Wins

Kotter’s sixth step emphasises the importance of generating short-term wins: early achievements that validate the transformation effort and build organisational momentum. These wins provide tangible proof that the change is delivering value and serve to convince sceptics, energise participants, and reward early adopters.

At TME, short-term wins were strategically cultivated through targeted use cases, fast-tracked pilots, and interactive initiatives like hackathons. “We organise a hackathon where the goal is to get a working prototype at the end of three days,” one stakeholder explained. These events not only produced visible results, but also served as experiential learning moments (Interview B).

One key strategy was starting with projects with existing buy-in and clear business value. “We started with the low hanging fruits for which we already had the buy-in,” a stakeholder noted. This approach helped the transformation team generate quick wins without excessive negotiation or risk (Interview A).

The impact of these early successes was more than technical—it was also symbolic and motivational. “It’s positive reinforcement. Give them an opportunity to shine through, to be recognised and gain visibility” (Interview B). This reflection underscores the dual function of short-term wins: they validate the approach and encourage broader participation. This is aligned with Kotter’s assertion that short-term wins provide opportunities to celebrate and reward those working for change.

Interviewee E noted “the people that are taking those projects and making it happen are our best ambassadors”. Others described how “they can get inspiration from others that have built something”. In one case, “a business counterpart met a data scientist from another organisation and [wanted] him on his project” (Interviewee B). These moments of cross-pollination illustrate how wins can spark new collaborations and stimulate broader involvement.

The strategic sequencing of adoption was also deliberate. “It’s about who to target first to make sure the others feel comfortable to take that role,” Interviewee J said. This aligns closely with Kotter’s guidance: target early adopters who are both credible and enthusiastic and use their progress to build trust and reduce resistance in others.

In summary, Toyota Motor Europe effectively used short-term wins to build early momentum for its Data Mesh transformation. These wins were not only proof-of-concept; they were stories, examples, and motivators. Kotter’s model stresses that visible success must be amplified and leveraged to sustain change. At TME, short-term achievements provided exactly that leverage: accelerating belief, participation, and the emergence of a supportive culture around decentralised data ownership.

4.2.7 Step 7: Sustain Acceleration

Kotter's seventh step emphasises the need to maintain momentum after early wins, ensuring that the transformation deepens, expands, and evolves rather than fading. Sustaining acceleration means building on existing success, resolving emerging friction points, and fostering institutional learning loops that allow adaptation and improvement over time.

At TME, sustaining progress required balancing structure with flexibility. One team member described the journey as iterative: "We had to simplify a lot of times. We continue improving and consequently getting feedback on the process and the issues people face" (Interview L). These learning cycles were supported by recurring forums such as practical experience-sharing meetings initiated by the Data Mesh team, which allowed teams to voice challenges, compare approaches, and adjust their practices.

Several interviewees highlighted that acceleration improved with familiarity and repetition. "There is a learning curve. Of course, the first data product will take more time, but then that lead time is going to become shorter and shorter" (Interview P). This reflects Kotter's point that success breeds momentum: once people see progress, they are more likely to continue.

The transformation also retained an organic character. "We move forward more in an organic way," said one stakeholder, capturing the balance between formal plans and emergent progress (Interview E).

In summary, acceleration at TME was driven through a combination of repeatable wins, ongoing feedback, and a willingness to adapt. At the same time, as Kotter cautions, celebrating too early can undermine momentum. TME's iterative improvement cycles and learning forums helped guard against this risk. Notably, the transformation retained an organic character, evolving less through rigid planning than through emergent coordination and experiential learning. This dynamic, decentralised mode of progress reflects the nature of Data Mesh itself, suggesting that sustaining acceleration may require not only structure, but also space for bottom-up growth and adaptation.

4.2.8 Step 8: Institute Change

Kotter's final step calls for change to be institutionalised, that is, embedded into the organisation's structure, processes, and culture so that it persists beyond the original transformation team. This means ensuring that the new behaviours are reflected in routines, roles, and reward systems, and that they continue even as people and priorities evolve.

At Toyota Motor Europe, several signs indicate that the Data Mesh transformation is beginning to take root structurally and culturally. One concrete step was the launch of a monthly meeting that brings together IT, business stakeholders, and external vendors. “We also invite people from other organisations within TME,” one participant explained, “we have all levels—VPs, managers, specialists, etc.” (Interview B). These recurring rituals are important not only for alignment, but also for continuity and collective memory.

Perhaps most importantly, some business teams have begun to incorporate Data Mesh responsibilities into formal planning processes. “In the beginning, it was work on top for them,” one interviewee recalled. “Now they have incorporated it in their yearly target planning” (Interview C). This shift indicates that Data Mesh is no longer seen as a side initiative but is becoming part of the expected contribution of certain roles.

Community learning practices also play a role in institutionalisation. “We launched sessions where data scientists are explaining projects to other data scientists,” one stakeholder shared (Interview C). These peer-to-peer forums reinforce shared language, common practices, and the idea that transformation is not just top-down but socially reinforced within technical communities.

In summary, while not yet fully institutionalised, the Data Mesh transformation at TME is moving in the right direction. Through recurring rituals, structural alignment, and integration into performance planning, the change is beginning to reshape how the organisation operates. Kotter cautions that new behaviours are vulnerable to degradation unless they become embedded in shared values and norms once the initial pressure for change subsides. Two factors are especially critical: showing how the new approach has improved performance and ensuring that “the next generation of management personifies the new approach”. At TME, the foundation for this cultural anchoring is actively being laid, with early adopters and business units beginning to serve as role models for a federated, data-driven way of working.

4.3 Emergent Challenges and Enablers

While Kotter’s 8-Step Model provides a structured lens through which to analyse the Data Mesh transformation at TME, it does not fully capture the emergent, relational, and context-specific dynamics observed. Many interview insights cut across multiple steps or revealed tensions that the model only partially anticipates. Rather than treating these as peripheral, this section highlights four cross-cutting themes that expose important undercurrents of the transformation—particularly where Kotter’s model under-specifies or remains silent. These include tensions in ownership and

motivation, the business-IT divide, the complexity of data products, and the organic nature of change.

4.3.1 Tensions in Ownership and Motivation

One of the most common issues expressed in the interviews is the reluctance or hesitation among business stakeholders to fully embrace data ownership. Although the transformation aspires to decentralise accountability, this shift is not always welcomed. “We are saying: ‘You are the data product owner,’ and they reply: ‘No, I just want to report’” (Interview F). This resistance was not based on opposition to the transformation itself, but on uncertainty about what the role entailed, how it would be supported, and whether it fit into existing workloads.

This raises questions not just about capability but about intrinsic and extrinsic motivation. One participant illustrated this tension with a metaphor. “Let’s imagine I am riding a bike, and you present to me a taxi. I love the idea. But now you give me a car and you tell me to drive it. That’s where my interest stops” (Interview M). The analogy conveys enthusiasm for the promise of Data Mesh, coupled with reluctance to assume the responsibilities it entails. Another noted, “IT sells it a bit too easily,” suggesting that the narrative around empowerment may obscure the real burden that new roles entail (Interview D). One stakeholder noted that while the roles were clear on paper, “I just don’t think I am that person” (Interview K).

At its core, this theme reflects the tension between desired cultural change and actual motivational structures. Ownership is not only a matter of assigning responsibility but of creating meaning and pride in that responsibility, conditions that must be cultivated through recognition, support, and narrative. Sometimes it is a cultural journey: “The business wants it, but in a silver platter,” one interviewee remarked, “which is the difficulty for anyone that tries to implement it, no matter how user friendly and easy it is” (Interview J).

4.3.2 The Business-IT Divide

A recurring tension in Toyota Motor Europe’s Data Mesh implementation was the disconnect between business and IT teams: a challenge that surfaced not only in communication, but in expectations, ownership, and execution. This divide was not antagonistic, but structural: each side approached the transformation with different assumptions about roles, responsibilities, and value.

From the business perspective, many participants expressed difficulty to understand the technical framework of Data Mesh. “We presented the concept of data product, governance, roles, etc., but it

lands pretty difficult as the explanations are still pretty technical,” one stakeholder recalled (Interview F). Another explained that even after multiple meetings, “I still don’t have a clear view of it... when you work on a daily basis, you think about your project, not the big picture” (Interview L). These comments highlight a gap in abstraction: the business understood their data needs, but not the architectural model proposed to meet them.

Meanwhile, IT teams often believed they were providing sufficient support. “We came prepared, theoretically it makes sense,” one IT lead explained, “but working with [the business], I saw the process evolving to a more flexible, customer-oriented way, not just pure theory” (Interview G). This shows a growing recognition that the implementation required adaptation and iteration, but also underscores the difficulty of translating technical design into something actionable and intuitive for non-technical stakeholders.

Business stakeholders may also struggle to articulate what they need or envision. As one participant put it, citing Henry Ford, “If I had asked people what they wanted, they would have said faster horses.” Another reflected, “I think that people with whom we had meetings from IT truly believed that they were helping us, but they were just making things more confusing” (Interview G). These comments highlight a broader translation gap: even when intentions are aligned, misunderstanding persists when roles, expectations, and language are not.

In short, the Data Mesh transformation at TME showed that technical support is not enough. Without real efforts to build mutual understanding and connect the technical and business sides, even a well-designed framework can struggle. As things progressed, this gap got smaller, but it still remained one of the main challenges.

4.3.3 The Complexity of Data Products

One of the most frequently cited difficulties in Toyota Motor Europe’s Data Mesh implementation was the abstract nature and perceived complexity of data products. While the central team provided definitions, journey maps, and onboarding materials, many business stakeholders found the concept difficult to internalise, particularly when it came to understanding how to start or what a “complete” data product should look like.

Several interviewees described the early materials as dense or overwhelming. “The initial workload is scary, we throw at you this big Excel file with hundreds of lines,” one stakeholder recalled (Interview I). Another remarked that while the documentation was available, “they hand it over

saying: ‘You need to prepare all of this before you can start talking to us’” (Interview F). These experiences created a sense of hesitation, even among motivated teams.

A recurring issue was that the term “data product” did not feel intuitive or actionable to business users. “A data product can be different things,” one person reflected, “which is good feedback, but it doesn’t help us understand what we should do” (Interview M). Another added, “Everybody understood the concept, but they couldn’t find the immediate steps to start with” (Interview K). These quotes suggest that the complexity was not just technical, but conceptual and procedural.

Even teams who were open to the model encountered confusion over where a data product starts and ends, and who should do what. “There are two challenges: the data products may or may not need all the data points we have in the domain,” one person said, “and we ask the Data Product Owner to list attributes, but it’s kind of technical terms for them” (Interview K). This points to a persistent ambiguity between data architecture language and business logic.

Moreover, the effort required to get started was often underestimated. This led to delays, and in some cases, abandonment of initial efforts, especially when other operational tasks competed for attention.

In summary, while the notion of data products is central to Data Mesh, Toyota’s experience illustrates that the concept must be continually clarified, contextualised, and simplified. Without sustained effort to demystify the term, support first actions, and tailor guidance to different domain levels, the concept risks being understood in theory but not enacted in practice.

4.3.4 The Organic Nature of Change

One of the most distinctive features of Toyota Motor Europe’s Data Mesh implementation was the tension between structured planning and organic evolution. While the initiative was launched with a clear strategy and governance framework, many aspects of the transformation evolved in practice through local experimentation, iterative adjustment, and informal problem-solving.

Several interviewees described the process as emergent rather than prescriptive. “We move forward more in an organic way,” one stakeholder observed (Interview E). This perspective reflects a transformation that was as much discovered as it was designed, with domain teams navigating complexity in real time. As one participant put it, “Implementing Data Mesh is learning by doing; not only using the references but also testing what is working for us” (Interview K).

This emergent character was both a strength and a constraint. On the one hand, it allowed flexibility, responsiveness, and a sense of co-creation. On the other hand, the lack of standardised processes sometimes created confusion or inertia, especially for teams that expected more prescriptive guidance: “We discussed with the Data Mesh team hoping for best practices on how to build data products, but they said it's up to you.” (Interview F)

Structural instability added to the challenge. “You can't create an architecture that reflects perfectly the organisation chart at time T,” one interviewee explained, “because in one or two years maybe the task force created to build this data product won't exist anymore” (Interview G). This illustrates how cross-functional efforts can be difficult to sustain, particularly when built on temporary teams or evolving mandates.

In summary, the Data Mesh transformation at TME revealed the need to balance structure and emergence. While governance frameworks and formal guidance are essential, federated models also require adaptability, learning, and room for organic growth. The most effective change trajectory is not entirely planned or entirely improvised, but one that can continuously iterate, learn from itself, and scale what works.

5 Discussion and Framework Development

5.1 Deriving the Framework

The empirical findings presented in Chapters 4.2 and 4.3, mapped respectively to Kotter's original steps and to broader organisational dynamics, reveal both the utility and limitations of classical change models in the context of Data Mesh. While Kotter's 8-Step Process offers a valuable structure for understanding organisational change, several tensions emerged at Toyota Motor Europe that point to the need for adaptation.

In particular, the transformation unfolded in a decentralised, iterative, and context-specific manner. Domains progressed at different speeds, ownership was unevenly assumed, and architectural visions often required local translation before gaining traction. Role adoption, rather than being a matter of simple empowerment, depended on targeted enablement strategies, peer support, and narrative legitimacy. Moreover, the process was marked less by linear execution than by emergent learning and hybrid leadership, underscoring the importance of flexibility, cultural alignment, and bottom-up momentum.

These insights suggest that while Kotter's steps remain relevant, their application in federated environments such as Data Mesh requires reframing. The Data Mesh Change Enablement Framework developed in this section builds on these patterns and reinterprets Kotter's logic to reflect the lived experience of transformation at Toyota.

The resulting framework aims to offer a coherent yet flexible guide for organisations navigating the sociotechnical challenges of Data Mesh adoption. Rather than a rigid sequence, the steps are best understood as reinforcing mechanisms that support behavioural change across multiple domains and levels of governance.

5.2 The Data Mesh Change Enablement Framework

While Kotter's 8-Step model provided a useful analytical support, this thesis goes beyond application. The empirical insights gathered at Toyota Motor Europe suggest that decentralised transformations such as Data Mesh require specific adaptations to classical change models. In particular, this study reveals that the unit of change is not a central team but a distributed network of domains. As such, steps like "build a guiding coalition" must occur at two distinct levels, executive and domain, which are not anticipated in Kotter's original formulation. Likewise, "create urgency" and "empower action" must account for asymmetries in motivation and capability across roles. The

resulting ‘Data Mesh Change Enablement Framework’ is thus not merely derived from Kotter; it represents a contextual extension that aligns better with federated, cross-domain settings.

5.2.1 Step 1: Reframe Urgency

A key insight from the empirical data is that urgency must be locally meaningful to activate change in decentralised environments. Rather than relying on abstract imperatives or top-down messaging, the first step of the adapted framework emphasises reframing urgency in a way that resonates within each domain. This contrasts with Kotter’s more general formulation, highlighting the need for emotional relevance alongside strategic clarity.

At Toyota, business representatives often acknowledged operational inefficiencies (siloed reports, duplicated metrics, and slow response times) but did not connect these pain points to the proposed shift in ownership. “We have more needs for data than we had before,” one stakeholder remarked, “but the solution still feels like an IT thing” (Interviewee E). This disconnection underscores the importance of reframing urgency from the ground up: business stakeholders must see themselves not only as beneficiaries of change, but as agents whose participation is essential. Storytelling plays a key role here. Highlighting domain-specific anecdotes (such as two teams independently building the same KPI) makes the consequences of centralisation more immediate.

Additionally, this step recommends the use of local metrics and cost-of-inaction framing to reinforce urgency. For instance, demonstrating how much time a business unit spends each month reconciling inconsistent data can be more persuasive than global platform KPIs.

Ultimately, reframing urgency means ensuring that the case for change is not only communicated, but experienced. Business domains must not be told why they should care, they must feel the consequences of staying the same.



Figure 2 – Evolution of Step 1

5.2.2 Step 2: Build a Multi-Layered Coalition

Building cross-functional support proved critical at TME, but rather than relying on a single, central coalition, transformation advanced through layered and distributed leadership. The adapted framework recognises this by formalising a dual-level coalition strategy, integrating both strategic sponsors and operational translators. This evolution reinterprets Kotter’s coalition step for federated contexts, where influence must be both vertical and horizontal.

As highlighted in Section 4.3.2, Toyota’s Data Mesh initiative revealed a persistent communication gap between the centralised platform team and decentralised domain stakeholders. Business actors often struggled to engage with architectural concepts and new roles, perceiving the transformation as IT-driven. Several interviewees underscored the importance of translation, pointing to individuals who, though not formally recognised, were able to interpret needs across technical and business boundaries. One stakeholder noted that “our IT counterpart was able to identify what data product we needed,” while another emphasised the emerging role of “Data Citizens”, business professionals with enough data fluency to collaborate effectively (Interviewee H).

The adapted framework proposes formalising these translation roles as part of a structured coalition. Organisations should nominate cross-functional leads from both business and IT, ensuring they are empowered with visibility, skills, and decision rights.

In short, building a translation-capable coalition is not only about identifying change agents, but it also requires institutionalising their collaboration across organisational layers. Successful Data Mesh transformations rely on a multi-layered coalition that combine executive sponsorship with embedded hybrid actors. This layered approach enables strategic alignment at the top and operational translation on the ground, ensuring the transformation is both credible and actionable.



Figure 3 – Evolution of Step 2

5.2.3 Step 3: Materialise the Vision

The vision of Data Mesh must move beyond architectural principles to become something people can act on. At TME, abstract terms like “data as a product” often slowed down momentum. The framework’s third step thus centres on materialising the vision: co-creating tangible, localised guidance that translates ideals into first actions. This adapts Kotter’s vision step to environments where cognitive overload and role uncertainty are key barriers.

A core issue was the abstract and cognitively demanding nature of the “data product” concept. While central teams provided definitions, journey maps, and onboarding materials, business users frequently found them overwhelming or inaccessible.

This created a paradox: the vision was theoretically understood but procedurally paralysing. Stakeholders struggled to answer basic questions such as “Where do we start?”, “What does a complete data product look like?”, and “Who is responsible for what?” Several noted that the term “data product” could mean many things, but this flexibility, rather than helping, added confusion.

These findings point to a critical shortcoming: vision alone is not empowering unless it is contextualised, sequenced, and humanised. The adapted framework therefore recommends materialising the vision, not just by handing over static artefacts, but by working with domains to co-create simplified, localised, and role-sensitive guidance. This may include interactive walkthroughs, prioritised starter kits, real-world examples, and progressive onboarding mechanisms that allow teams to grow into their responsibilities.

In sum, materialising the vision is about turning a strategic ideal into a practical entry point. Without this, even the most compelling vision may remain suspended between understanding and execution.



Figure 4 – Evolution of Step 3

5.2.4 Step 4: Translate the Message

Effective communication in decentralised change is less about transmission and more about translation. At TME, the message of Data Mesh only gained traction when adapted by peers and embedded actors into context-specific narratives. The fourth step of the adapted framework thus shifts from “communicate the vision” to “translate the message,” acknowledging that resonance emerges through dialogue, not dissemination.

To address this, the adapted framework reframes communication as a bidirectional flow. Translation does not mean simplifying PowerPoint slides; it means engaging business actors in sensemaking. Peer-led storytelling, domain-specific use cases, and horizontal communities of practice proved more impactful than centrally crafted narratives. As one interviewee put it, “you need to explain it like it’s the first time someone hears it.”

This step therefore emphasises audience-sensitive adaptation and co-creation of narratives. Communication should begin with listening: to domain-specific concerns, levels of fluency, and existing workflows. It should then proceed in layers, combining high-level framing with use-case demos, playbooks, and peer testimonials. Most importantly, it should empower recipients to reshape and share the message themselves. A message is only owned when it is repeated in the recipient’s own terms.

In a federated environment like Data Mesh, translating the message is not the responsibility of a communications team alone, but of embedded actors, hybrid profiles, and feedback-rich structures that enable meaning to emerge with and through the audience.

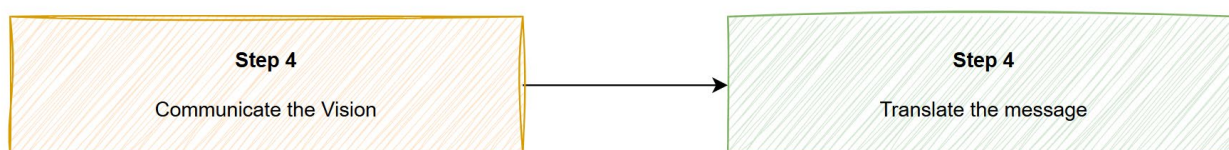


Figure 5 – Evolution of Step 4

5.2.5 Step 5: Empower Domains for Ownership

Empowerment in a Data Mesh context goes beyond removing structural barriers—it requires enabling domains to take true ownership of data responsibilities. At TME, the absence of tooling maturity or role clarity often stopped domain initiative. This step reinterprets Kotter’s call to

“empower broad-based action” by shifting the focus toward capability-building, negotiated accountability, and psychological safety within each domain. Empowerment must be earned, not merely granted.

As seen in Section 4.3.1, several Toyota business stakeholders were named Data Product Owners or Stewards but felt unprepared or unsure of what to do. To address this, the framework calls for building structured support around each role, training, clear expectations, and time to learn through practice. Mentorship and peer support also played an important role at TME, helping people grow into their responsibilities gradually.

Another point is that ownership is often seen as extra work, not an opportunity. As one stakeholder put it, “In the beginning it was work on top for them.” This perception came from unclear value, lack of support, and poor communication about the benefits. Framing ownership as a way to improve autonomy and relevance is key.

Finally, enablement also requires platform choices that match user needs. One team member explained that “the tools we selected are no/low code so business profiles can use it without any technical knowledge” (Interview B). Without this, even willing teams would struggle to contribute.

In summary, empowering domains for ownership means helping people act, not just telling them to own. It requires support, clarity, and framing, so that ownership becomes something teams feel ready for, not something they push back against.



Figure 6 – Evolution of Step 5

5.2.6 Step 6: Showcase Early Wins

While Kotter stresses “short-term wins” to build credibility and momentum, the TME case revealed that progress often unfolded incrementally and unevenly across domains. Success was not always immediate or easily measurable, yet stories of local experiments, however modest, proved instrumental in sustaining engagement. This step reframes wins not as predefined targets but as organic signals of movement, tailored to context and shared through informal channels to build legitimacy.

As one stakeholder explained, “the people that are taking those projects and making it happen are our best ambassadors.”. Another added, “Showing that there are success stories already” helped others believe they could do the same.

The framework thus reframes this step as showcase early wins, not just generating value, but deliberately surfacing and sharing it. Stories of progress, even if incomplete, help demystify the change and lower the perceived barrier to entry.

These early wins also drive peer influence. This creates a ripple effect, where early adopters become credible, visible proof that the model works.

In sum, early wins matter not just for validation, but for momentum. A Data Mesh transformation that fails to make local progress visible risks to slow down. But when those small wins are amplified and linked to the broader vision, they create the cultural traction that long-term change depends on.

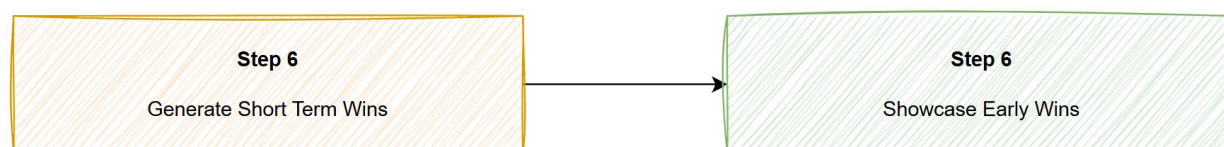


Figure 7 – Evolution of Step 6

5.2.7 Step 7: Institutionalise Learning Loops

Traditional change models advocate against declaring victory too early. At TME, rather than a centralised acceleration plan, momentum was maintained through ongoing peer exchanges, feedback loops, and role-modelling across domains. This step modifies Kotter’s “sustain acceleration” by emphasising decentralised reinforcement and emergent initiatives rather than top-down planning.

At TME, early progress emerged through experimentation. “Implementing Data Mesh is learning by doing,” one interviewee explained. This reflected a healthy culture of iteration but also revealed a gap: learning was active, but not always captured or shared beyond individual teams. To address this, the framework encourages formalising what already happens informally. Regular communities of practice for roles like Data Product Owner and Domain Steward allow peers to exchange insights and refine common standards.

TME's case also shows that learning requires time and institutional support, not just goodwill. "In the beginning, it was work on top for them," one participant recalled. Without explicit space for reflection, even motivated teams can feel isolated or overloaded.

In short, learning is not just a byproduct of transformation, it is the transformation. When loops are in place, change becomes both scalable and adaptive. Domains no longer operate in isolation but contribute to, and benefit from, a growing base of collective intelligence.

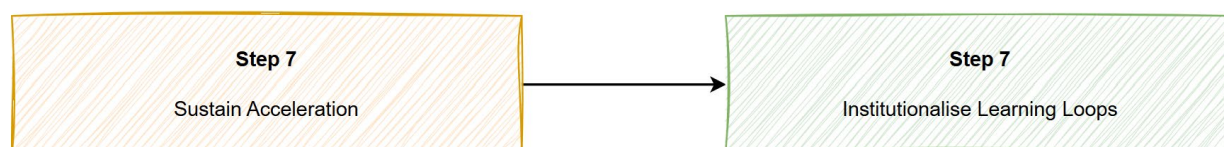


Figure 8 – Evolution of Step 7

5.2.8 Step 8: Embed New Roles in Governance

Institutionalising change in a federated setting means embedding new roles, not just into process flows, but into the governance fabric itself. At TME, sustaining the Data Mesh transformation required that roles like Data Product Owner and Domain Data Steward be formalised in evaluation, training, and steering routines. This step reinterprets Kotter's "institutionalise change" as an effort to anchor distributed responsibility within durable organisational mechanisms without reverting to central control.

The adapted framework reframes this final step as embed new roles in governance. It emphasises integrating these new roles into HR systems, planning cycles, and governance processes. Some positive signs were already visible at Toyota. Teams created journey maps to clarify data product development. The data marketplace was seen as a marker of maturity: "Anything that is in the marketplace means someone has accepted ownership and the documentation is there."

Still, these practices remained isolated. For Data Mesh to be sustainable, legitimacy must be institutional. Ownership should be expected, supported, measured, and rewarded across domains and levels. As Kotter reminds us, change is not real until it becomes routine. In Data Mesh, routine means the new roles are no longer exceptional, they are embedded in how the organisation works.

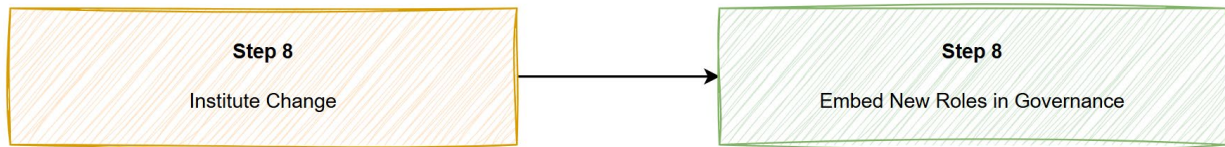


Figure 9 – Evolution of Step 8

Together, these eight adapted steps form the Data Mesh Change Enablement Framework: a response to the practical and organisational realities observed at Toyota Motor Europe. The framework builds on Kotter’s logic while reorienting each step around the needs of decentralised teams, unfamiliar roles, and emergent learning. Rather than offering a fixed blueprint, it proposes a flexible sequence of interventions to help organisations transition from centralised control to federated data ownership. The next chapter reflects on the broader significance of these findings and outlines directions for future research and application.

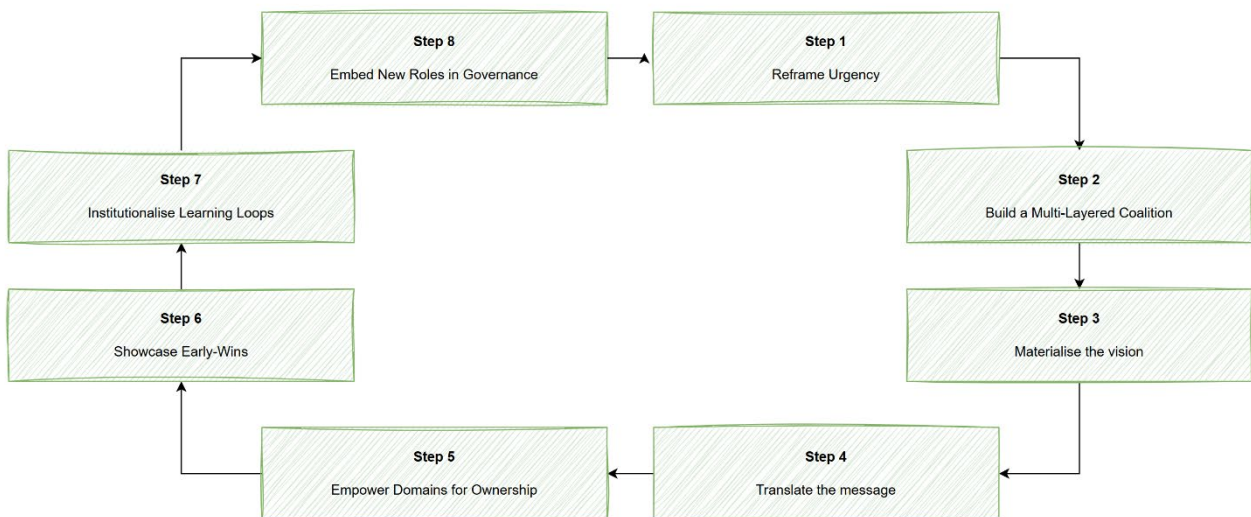


Figure 10 – The Data Mesh Enablement Framework

5.3 Validation and Practical Implications

The Data Mesh Change Enablement Framework is not presented as a universally validated model, but as a conceptual contribution derived from empirical findings. It reflects the lived experiences, tensions, and strategies observed at Toyota Motor Europe during a large-scale decentralised data transformation. Its structure and content were informed abductively: emerging through a cyclical process of interpreting interview data and iteratively refining theoretical constructs.

5.3.1 Empirical Grounding

The eight adapted steps of the framework emerged abductively from recurring patterns in the empirical data. For instance, the emphasis on enablement over empowerment directly reflects repeated concerns among interviewees who felt unprepared or unsupported in their new responsibilities. Similarly, the notion of multi-level coalitions arose from the recognition that high-level initiatives sometimes fail to resonate with business stakeholders. Business actors are more likely to engage when change is championed by peers who operate at the same level, face similar challenges, and speak a shared operational language. Embedding informal champions within each domain creates proximity, relevance, and trust, key ingredients for driving behavioural change in decentralised contexts.

The framework was iteratively shaped through triangulation across different stakeholder perspectives, including business users, IT leads, and data governance specialists. Its logic reflects convergence across these groups: the same friction points (such as role ambiguity, support gaps, or translation barriers) surfaced in multiple interviews, even when phrased differently depending on organisational role. These patterns strengthen the claim that the framework is not arbitrarily constructed but grounded in shared lived experience.

5.3.2 Framework as a Practical Tool

The framework serves as a practical instrument for structuring onboarding strategies within decentralised data initiatives. Rather than offering prescriptive instructions, it provides a modular and sequenced view of the enablers that support role clarity, stakeholder engagement, and behavioural reinforcement in Data Mesh environments.

Its flexibility makes it suitable for environments where adoption unfolds at different speeds. In a federated setup like Toyota's, each domain advances at its own pace depending on factors such as local leadership, resource availability, or prior experience with data ownership. Some domains may move quickly through the early steps, while others take more time to build foundational understanding or secure buy-in. The framework accommodates this variation by offering a coherent path without imposing a rigid timeline.

It can also be used retroactively, as a diagnostic tool to identify which change mechanisms are missing or underdeveloped in a given context. This allows teams to reflect on past efforts and make targeted adjustments based on their current stage.

Importantly, the framework positions change enablement as a distributed responsibility, not confined to a central change office or platform team. It promotes local ownership of role definition, peer mentoring, and knowledge-sharing infrastructure, aligning with the underlying logic of decentralised governance.

Beyond its immediate utility, the framework contributes to the broader discourse on decentralised data governance by foregrounding the social, behavioural, and procedural dimensions of Data Mesh. While most existing literature centres on architecture and platform design, this framework helps operationalise the organisational side of transformation. It provides a structured sequence of interventions that can support practitioners in building communities of practice, shifting mindsets, and enabling local ownership. By doing so, it bridges the gap between abstract change models and real-world onboarding challenges in federated environments.

5.3.3 Boundary Conditions

While the Data Mesh Change Enablement Framework provides a structured approach to onboarding decentralised data roles, its applicability depends on specific organisational conditions. First, the framework assumes a willingness to distribute data responsibility. In highly centralised organisations, its enablers may face resistance or fail to activate.

Second, the framework emerged from a single case context shaped by Toyota Motor Europe's scale, regulatory exposure, and existing digital infrastructure. While the principles may be relevant beyond that setting, their sequence and impact may vary in smaller firms, less mature data environments, or industries with different governance norms.

Third, the framework focuses specifically on organisational enablement. It does not address the technical foundations of Data Mesh, such as platform architecture or data infrastructure. As such, it should be used in parallel with technical roadmaps.

Finally, because Data Mesh transformations are iterative by nature, the framework is not intended as a one-time rollout. Domains may revisit certain steps multiple times as needs evolve. Its value lies in guiding locally situated progress, not enforcing linearity or uniformity.

6 Conclusion

This thesis explored how large organisations can enable the successful onboarding of business stakeholders into the decentralised roles introduced by Data Mesh. While Data Mesh has gained traction as a technical and architectural paradigm, its organisational implications, and particularly the human side of decentralising data responsibility, remain underexplored. Through a literature review, a qualitative case study at Toyota Motor Europe, and the development of a change enablement framework, this research aimed to bridge that gap.

6.1 Answering the Research Questions

Main RQ: How can organisations effectively manage the onboarding of business-domain stakeholders into their new roles and responsibilities during a Data Mesh implementation?

This thesis finds that successful onboarding requires more than structural design or role assignment. It demands an intentional, adaptive change enablement approach rooted in organisational realities. The proposed Data Mesh Change Enablement Framework outlines eight mechanisms to support this process: reframing urgency, building a multi-layered coalition, materialising the vision, translating the message, empowering domains for ownership, showcasing early wins, institutionalising learning loops, and embedding new roles in governance.

Sub-RQ1: What organisational challenges emerge when onboarding business teams into decentralised data ownership roles?

The case study at Toyota Motor Europe revealed a consistent set of challenges: role ambiguity, uneven motivation across domains, resistance to ownership, and misalignment between central messaging and local needs. These frictions were amplified by cultural and structural inertia, and by the difficulty of translating technical frameworks into business-relevant responsibilities.

Sub-RQ2: How do business stakeholders understand, embrace, or resist the roles of DATA Product Owner and Domain Data Steward?

Stakeholder responses varied widely. Some embraced their new roles as opportunities for influence and impact, while others rejected the additional workload or struggled to understand their responsibilities. Several interviewees expressed discomfort or scepticism, reflecting a lack of psychological ownership. These reactions highlight the need for active enablement, not just formal assignment of titles.

Sub-RQ3: In what ways can Kotter’s 8-Step Process be adapted to address the organisational challenges of Data Mesh environment?

While Kotter’s model provided a useful starting point, its top-down and linear assumptions proved insufficient in federated contexts. The adapted framework reframes several steps—for instance, recasting “urgency” as a contextual narrative and “coalitions” as multi-layered structures involving hybrid actors. It preserves the core logic of change mobilisation but reshapes it for decentralised, domain-led transformations.

Sub-RQ4: What organisational enablers, beyond technical infrastructure, support sustained business role adoption in a Data Mesh environment?

Non-technical enablers included hands-on mentorship, low-code tools to lower the barrier to entry, peer storytelling to share best practices, and governance structures that legitimised new roles. Domains that received targeted support, both emotional and procedural, were more likely to adopt their responsibilities and integrate them into ongoing routines.

6.2 Limitations

While this thesis provides novel insights into the organisational dynamics of Data Mesh transformation, several limitations must be acknowledged to properly situate its contributions.

First, the research is based on a single case study at Toyota Motor Europe. Although TME offers a rich and complex setting, the findings are shaped by its specific organisational structure, culture, and regulatory environment. As such, generalisability to other contexts, particularly smaller organisations or those with lower data maturity, may be limited.

Second, the study captures a snapshot of an ongoing transformation. It focuses primarily on early and mid-stage dynamics of role onboarding, without covering long-term sustainability, performance measurement, or institutional anchoring.

Third, the scope of analysis is deliberately focused on the “people side” of Data Mesh. While this enabled a deep dive into change enablement, it excludes technical implementation aspects such as platform design, data architecture, or engineering practices.

Finally, the abductive and qualitative methodology introduces interpretive subjectivity. Despite efforts to triangulate findings across roles and validate insights iteratively, the resulting framework reflects the researcher’s analytical framing as much as empirical input.

These limitations do not undermine the study's relevance, but they define its boundaries. The findings should be seen as exploratory and theory-building, offering a foundation for refinement, contextual adaptation, and validation in future research.

6.3 Directions for Future Research

Future studies could investigate the framework's applicability in other organisational contexts. While the insights were grounded in Toyota Motor Europe's transformation, the conditions that shaped them (cross-functional disconnects, asymmetrical motivation, and decentralised operating models) are not unique. Comparative case studies in other industries or geographies would help determine which elements of the framework are transferable and which require contextual adaptation. Such research would enhance its robustness and provide sector-specific recommendations.

Second, longitudinal studies could explore how new roles such as Data Product Owner and Domain Data Steward evolve over time. This thesis captured a snapshot during early and transitional phases, but questions remain about long-term role legitimacy, sustained engagement, and the institutional anchoring of decentralised data responsibilities. Tracking these roles across time would yield valuable insights into the durability of onboarding strategies and the life cycle of federated governance.

Finally, Data Mesh is as much a cultural and behavioural shift as it is a technical one. Future work could explore the interplay between platform capabilities (e.g. self-serve infrastructure, data discovery tools) and organisational dynamics (e.g. motivation, autonomy, trust). Understanding these interdependencies would help clarify how tooling choices enable—or constrain—business-side ownership.

Together, these directions would strengthen both the theoretical foundation and the practical relevance of the proposed framework, helping future organisations navigate the complexity of decentralised data transformation more effectively.

6.4 Final Reflection

This thesis began with a simple question: how can organisations enable business stakeholders to step meaningfully into the decentralised roles required by Data Mesh? As the research unfolded, it became clear that this challenge is not primarily technical, but organisational. It is not only about

designing new architectures or roles, but about preparing people to interpret, accept, and enact new forms of responsibility.

The case of Toyota Motor Europe illustrated this vividly. While the transformation was backed by a strong architectural vision and strategic intent, its success hinged on far more grounded dynamics: trust, clarity, support, and communication. Domains progressed not because they were told to, but because they found ways: sometimes improvised, sometimes supported, to make the change meaningful within their local realities.

In response to this, the thesis proposed the Data Mesh Change Enablement Framework: an adaptation of Kotter's 8-Step model tailored to the realities of federated organisations. Rather than prescribing a linear rollout, the framework encourages locally adapted pathways to change, built on enablement, peer learning, and iterative feedback. Its intent is not to replace architectural thinking, but to complement it with an equally rigorous focus on human systems.

This final reflection is therefore also a call to action. For organisations embarking on Data Mesh or similar decentralised transformations, the question is not just "How do we design the platform?" but "How do we help people grow into the roles the platform requires?" Architecture alone cannot carry the weight of change. It must be supported by mechanisms that make ownership possible, legitimate, and sustainable.

The journey at Toyota is still unfolding. But its early lessons already suggest a broader truth: meaningful transformation happens not when everyone moves at the same speed, but when everyone is given the support to move meaningfully from where they are. This is the real work of change, and the opportunity that decentralised data strategies present.

References

- [1] I. Yaqoob *et al.*, ‘Big data: From beginning to future’, *International Journal of Information Management*, vol. 36, no. 6, Part B, pp. 1231–1247, Dec. 2016, doi: 10.1016/j.ijinfomgt.2016.07.009.
- [2] ‘High Data Growth and Modern Applications Drive New Storage Requirements in Digitally Transformed Enterprises - Dell’. Accessed: Jun. 03, 2025. [Online]. Available: <https://www.readkong.com/page/high-data-growth-and-modern-applications-drive-new-storage-7164884>
- [3] S. Genovese, ‘Data Mesh: the newest paradigm shift for a distributed architecture in the data world and its application’, laurea, Politecnico di Torino, 2021. Accessed: Mar. 08, 2025. [Online]. Available: <https://webthesis.biblio.polito.it/20415/>
- [4] A. A. Harby and F. Zulkernine, ‘From Data Warehouse to Lakehouse: A Comparative Review’, in *2022 IEEE International Conference on Big Data (Big Data)*, Dec. 2022, pp. 389–395. doi: 10.1109/BigData55660.2022.10020719.
- [5] I. Machado, C. Costa, and M. Y. Santos, ‘Data-Driven Information Systems: The Data Mesh Paradigm Shift’, *Proceedings of the International Conference on Information Systems Development (ISD)*, Aug. 2021, [Online]. Available: <https://aisel.aisnet.org/isd2014/proceedings2021/currenttopics/9>
- [6] ‘How to Move Beyond a Monolithic Data Lake to a Distributed Data Mesh’, [martinfowler.com](https://martinfowler.com/articles/data-monolith-to-mesh.html). Accessed: Feb. 11, 2025. [Online]. Available: <https://martinfowler.com/articles/data-monolith-to-mesh.html>
- [7] I. Araújo Machado, C. Costa, and M. Y. Santos, ‘Advancing Data Architectures with Data Mesh Implementations’, in *Intelligent Information Systems*, J. De Weerd and A. Polyvyanyy, Eds., Cham: Springer International Publishing, 2022, pp. 10–18. doi: 10.1007/978-3-031-07481-3_2.
- [8] A. Wider, S. Verma, and A. Akhtar, ‘Decentralized Data Governance as Part of a Data Mesh Platform: Concepts and Approaches’, in *2023 IEEE International Conference on Web Services (ICWS)*, Jul. 2023, pp. 746–754. doi: 10.1109/ICWS60048.2023.00101.
- [9] A. Kumar, A. Mishra, and S. Kumar, ‘Data Mesh’, in *Architecting a Modern Data Warehouse for Large Enterprises : Build Multi-cloud Modern Distributed Data Warehouses with Azure and AWS*, A. Kumar, A. Mishra, and S. Kumar, Eds., Berkeley, CA: Apress, 2024, pp. 161–174. doi: 10.1007/979-8-8688-0029-0_4.
- [10] A. Schwanke, ‘Data Mesh In Practice — Recommendations from Roche’s Journey’, Medium. Accessed: Mar. 18, 2025. [Online]. Available: <https://medium.com/@axel.schwanke/data-mesh-in-practice-recommendations-from-roches-journey-e0e0d51c4a89>
- [11] Flink Forward, *Netflix Data Mesh: Composable Data Processing - Justin Cunningham*, (Apr. 28, 2020). Accessed: May 20, 2025. [Online Video]. Available: https://www.youtube.com/watch?v=TO_IiN06jJ4
- [12] S. Panigrahy, B. Dash, and R. Thatikonda, ‘From Data Mess to Data Mesh: Solution for Futuristic Self-Serve Platforms’, *INTERNATIONAL JOURNAL OF ADVANCED RESEARCH IN COMPUTER AND COMMUNICATION ENGINEERING*, vol. 12, no. 4, Apr. 2023, doi: 10.17148/IJARCC.2023.124121.
- [13] A. Bedard, ‘The 8-Step Process for Leading Change | Dr. John Kotter’, Kotter International Inc. Accessed: May 04, 2025. [Online]. Available: <https://www.kotterinc.com/methodology/8-steps/>
- [14] M. E. M. El Aissi *et al.*, ‘Data Lake Versus Data Warehouse Architecture: A Comparative Study’, in *WITS 2020*, S. Bennani, Y. Lakhrissi, G. Khaissidi, A. Mansouri, and Y. Khamlichi, Eds., Singapore: Springer, 2022, pp. 201–210. doi: 10.1007/978-981-33-6893-4_19.

- [15] E. Hechler, M. Weihrauch, and Y. (Catherine) Wu, ‘Data Fabric and Data Mesh Research Areas’, in *Data Fabric and Data Mesh Approaches with AI: A Guide to AI-based Data Cataloging, Governance, Integration, Orchestration, and Consumption*, E. Hechler, M. Weihrauch, and Y. (Catherine) Wu, Eds., Berkeley, CA: Apress, 2023, pp. 375–392. doi: 10.1007/978-1-4842-9253-2_17.
- [16] I. Blohm, F. Wortmann, C. Legner, and F. Köbler, ‘Data products, data mesh, and data fabric’, *Bus Inf Syst Eng*, vol. 66, no. 5, pp. 643–652, Oct. 2024, doi: 10.1007/s12599-024-00876-5.
- [17] N. Miloslavskaya and A. Tolstoy, ‘Big Data, Fast Data and Data Lake Concepts’, *Procedia Computer Science*, vol. 88, pp. 300–305, Jan. 2016, doi: 10.1016/j.procs.2016.07.439.
- [18] M. Armbrust, A. Ghodsi, R. Xin, and M. Zaharia, ‘Lakehouse: A New Generation of Open Platforms that Unify Data Warehousing and Advanced Analytics’, 2021.
- [19] F. Nargesian, E. Zhu, R. J. Miller, K. Q. Pu, and P. C. Arocena, ‘Data lake management: challenges and opportunities’, *Proc. VLDB Endow.*, vol. 12, no. 12, pp. 1986–1989, Aug. 2019, doi: 10.14778/3352063.3352116.
- [20] D. Mazumdar, J. Hughes, and J. B. Onofre, ‘The Data Lakehouse: Data Warehousing and More’, Oct. 12, 2023, *arXiv*: arXiv:2310.08697. doi: 10.48550/arXiv.2310.08697.
- [21] I. A. Machado, C. Costa, and M. Y. Santos, ‘Data Mesh: Concepts and Principles of a Paradigm Shift in Data Architectures’, *Procedia Computer Science*, vol. 196, pp. 263–271, Jan. 2022, doi: 10.1016/j.procs.2021.12.013.
- [22] K. Kanagarla, ‘<p>Data Mesh: Decentralised Data Management</p>’, Jan. 18, 2024, *Social Science Research Network, Rochester, NY*: 5024895. Accessed: Mar. 05, 2025. [Online]. Available: <https://papers.ssrn.com/abstract=5024895>
- [23] V. K. Butte and S. Butte, ‘Enterprise Data Strategy: A Decentralized Data Mesh Approach’, in *2022 International Conference on Data Analytics for Business and Industry (ICDABI)*, Oct. 2022, pp. 62–66. doi: 10.1109/ICDABI56818.2022.10041672.
- [24] A. Goedegebuure *et al.*, ‘Data Mesh: a Systematic Gray Literature Review’, *ACM Comput. Surv.*, vol. 57, no. 1, pp. 1–36, Jan. 2025, doi: 10.1145/3687301.
- [25] M. R. Hasan and C. Legner, ‘UNDERSTANDING DATA PRODUCTS: MOTIVATIONS, DEFINITION, AND CATEGORIES’, 2023.
- [26] R. Eichler, C. Gröger, E. Hoos, H. Schwarz, and B. Mitschang, ‘From Data Asset to Data Product – The Role of the Data Provider in the Enterprise Data Marketplace’, in *Service-Oriented Computing*, J. Barzen, F. Leymann, and S. Dustdar, Eds., Cham: Springer International Publishing, 2022, pp. 119–138. doi: 10.1007/978-3-031-18304-1_7.
- [27] D. Joshi, S. Pratik, and M. Rao, ‘Data Governance in Data Mesh Infrastructures: The Saxo Bank Case Study’, *ICEB 2021 Proceedings (Nanjing, China)*, Dec. 2021, [Online]. Available: <https://aisel.aisnet.org/iceb2021/52>
- [28] C. Legner *et al.*, ‘Digitalization: Opportunity and Challenge for the Business and Information Systems Engineering Community’, *Bus Inf Syst Eng*, vol. 59, no. 4, pp. 301–308, Aug. 2017, doi: 10.1007/s12599-017-0484-2.
- [29] M. L. Markus, ‘Technochange management: using IT to drive organizational change’, *J Inf Technol*, vol. 19, no. 1, pp. 4–20, Mar. 2004, doi: 10.1057/palgrave.jit.2000002.
- [30] S. H. Appelbaum, S. Habashy, J. Malo, and H. Shafiq, ‘Back to the future: revisiting Kotter’s 1996 change model’, *Journal of Management Development*, vol. 31, no. 8, pp. 764–782, Jan. 2012, doi: 10.1108/02621711211253231.
- [31] S. Taneja, J. Humphreys, D. Anderson, L. Singleton, and M. G. Pryor, ‘Challenges Facing Change Management: Theories and Research’, *DBR*, vol. 9, no. 1, pp. 1–20, Jan. 2008, doi: 10.51768/dbr.v9i1.91200801.
- [32] Pierce, ‘The state of psychological ownership: Integrating and extending a century of research’, *Review of General Psychology*, vol. 7, no. 1, pp. 84–107, Mar. 2003, doi: 10.1037/1089-2680.7.1.84.

- [33] M. AlManei, K. Salonitis, and C. Tsinopoulos, 'A conceptual lean implementation framework based on change management theory', *Procedia CIRP*, vol. 72, pp. 1160–1165, Jan. 2018, doi: 10.1016/j.procir.2018.03.141.
- [34] H. Elsan Mansaray, 'The Role of Leadership Style in Organisational Change Management: A Literature Review', *JHRM*, vol. 7, no. 1, p. 18, 2019, doi: 10.11648/j.jhrm.20190701.13.
- [35] C. V. Brisson-Banks, 'Managing change and transitions: a comparison of different models and their commonalities', *Library Management*, vol. 31, no. 4/5, pp. 241–252, May 2010, doi: 10.1108/01435121011046317.
- [36] B. Joseph Galli, 'Change Management Models: A Comparative Analysis and Concerns', *IEEE Engineering Management Review*, vol. 46, no. 3, pp. 124–132, 2018, doi: 10.1109/EMR.2018.2866860.
- [37] S. Al-Haddad and T. Kotnour, 'Integrating the organizational change literature: a model for successful change', *Journal of Organizational Change Management*, vol. 28, no. 2, pp. 234–262, Apr. 2015, doi: 10.1108/JOCM-11-2013-0215.
- [38] S. Driessen, W.-J. van den Heuvel, and G. Monsieur, 'ProMoTe: A Data Product Model Template for Data Meshes', in *Conceptual Modeling*, J. P. A. Almeida, J. Borbinha, G. Guizzardi, S. Link, and J. Zdravkovic, Eds., Cham: Springer Nature Switzerland, 2023, pp. 125–142. doi: 10.1007/978-3-031-47262-6_7.
- [39] A. Dibouliya, 'Review on Data Mesh Architecture and its Impact', vol. 44, no. 7, 2023.
- [40] J. Bode, N. Kühn, D. Kreuzberger, and C. Holtmann, 'Toward Avoiding the Data Mess: Industry Insights From Data Mesh Implementations', *IEEE Access*, vol. 12, pp. 95402–95416, 2024, doi: 10.1109/ACCESS.2024.3417291.
- [41] R. Winter and T. Hackl, *Data Mesh at Scale - Exploration of current practices in large organizations*. 2023.
- [42] H. Kallio, A.-M. Pietilä, M. Johnson, and M. Kangasniemi, 'Systematic methodological review: developing a framework for a qualitative semi-structured interview guide', *Journal of Advanced Nursing*, vol. 72, no. 12, pp. 2954–2965, 2016, doi: 10.1111/jan.13031.
- [43] A. Dubois and L.-E. Gadde, 'Systematic combining: an abductive approach to case research', *Journal of Business Research*, vol. 55, no. 7, pp. 553–560, Jul. 2002, doi: 10.1016/S0148-2963(00)00195-8.
- [44] H. K. Klein and M. D. Myers, 'A Set of Principles for Conducting and Evaluating Interpretive Field Studies in Information Systems', *MIS Quarterly*, vol. 23, no. 1, pp. 67–93, 1999, doi: 10.2307/249410.
- [45] D. A. P. Alexander, 'LINCOLN AND GUBA'S QUALITY CRITERIA FOR TRUSTWORTHINESS', vol. 6, no. 4, 2019.
- [46] D. J. Paper, J. A. Rodger, and P. C. Pendharkar, 'A BPR case study at Honeywell', *Business Process Management Journal*, vol. 7, no. 2, p. 85, 2001, doi: 10.1108/14637150110389416.
- [47] J. P. Kotter, *Leading Change*. Harvard Business School Press, 1996.

Appendices

Appendix 1 – Interview Guide

The following interview guide was used to conduct semi-structured interviews with business and IT stakeholders involved in the Data Mesh transformation at Toyota Motor Europe. It was designed to explore perceptions of new data roles, onboarding processes, and change dynamics, and was aligned with the research questions and analytical framework presented in Chapter 3.

Table 2 – Interview Guide

Interview Guide	
Section 1 - Background and Context	
1)	Can you briefly describe your current role and responsibilities?
2)	How would you describe your involvement in the Data Mesh transformation at TME?
3)	When did you first hear about Data Mesh? What was your initial impression?
Section 2 - Role Clarity and Onboarding	
4)	Have you been assigned a formal role in the Data Mesh Initiative?
5)	How was this role explained to you?
6)	Were you given any training or onboarding materials?
7)	What, if any, was unclear or confusing about your role at the beginning?
8)	Did you have any prior experience that helped you take on this role?
Section 3 - Change Process and Support	
9)	Was there a clear business reason communicated for adopting Data Mesh?
10)	Were barriers to role adoption removed for you (e.g., time, resources)?
11)	Was there any support or mentorship to help you succeed in this role?
Section 4 - Cultural and Organisational Dynamics	
12)	How did your team adapt to this new idea of decentralised data ownership?
13)	Were there tensions between IT and business stakeholders in this process?
Section 5 - Reflections and Suggestions	
14)	What helped you most in adopting your role (if anything)?
15)	What would you have needed that was missing?
16)	If you were advising another company on how to onboard business stakeholders into Data Mesh roles, what would you recommend they do, or avoid doing?

Appendix 2 – Extracts from Interviews

Table 3 – Extracts from Interviews

Interview	Thematic	Citation
A	Build a Guiding Coalition	Where we do not get enough buy in from the business, we get the support of our management that go and talk with the (...)
B	Build a Guiding Coalition	We are the only team that has its dedicated communication specialist.
D	Build a Guiding Coalition	Somebody needs to take the lead in organising this and say: "this is where we are going to, and these are the next steps".
P	Build a Guiding Coalition	We have a data governance organisation, we have a council, a steering board, a community, some teams chat, etc.
E	Communicate the Vision	Community gathering, data governance community, etc.
P	Communicate the Vision	You can find the roles of the Data Mesh team, who is doing what and how these people are involved.
F	Communicate the Vision	We presented the concept of data product, governance, roles, etc. but it lands pretty difficult as the explanations are still (...)
K	Communicate the Vision	Everybody understood the concept, but they couldn't find the immediate steps to start with.
A	Create a Sense of Urgency	A year and a half earlier, we just had [...] the business intelligence competency centre.
B	Create a Sense of Urgency	Before, people were working in silos, doing their own solution for their team, not realising that there is so many things (...)
C	Create a Sense of Urgency	Teams are using the same data.
J	Create a Sense of Urgency	Data is locally stored; you need to find the right person and ask him to share it.
D	Empower Broad-Based Action	I think what you really need is some IT people who take you by the hand and help you go through it.
E	Empower Broad-Based Action	I try to fill the gaps where there were needs. It grew organically
F	Empower Broad-Based Action	We are saying: "You are the data product owner", they reply: "No I just want to report".
K	Empower Broad-Based Action	Some initiatives come from the entities, and then we use the concept of Yokoten, we set the same standard for other entities, (...)
B	Institute change	We also invite people from other organisations within TME, we have all levels (VPs, managers, specialists, etc.)
I	Institute change	In the beginning it was work on top for them. Now they have incorporated it in their yearly target planning.
C	Institute change	We launched sessions where Data Scientists are explaining projects to other Data Scientists.
K	Institute change	We found our domain based on our organisational structure, but we also created a kind of enterprise level domains. We create (...)
A	Short-Term Wins	We started with the low hanging fruits for which we already had the buy in.
B	Short-Term Wins	We organise a hackathon where the goal is to get a working prototype at the end of three days
J	Short-Term Wins	It's about who to target first to make sure the other feel comfortable to take that role.

Interview	Thematic	Citation
J	Short-Term Wins	Showing that there are success stories already.
A	Strategic Vision	The end goal is to have proper quality, governance, and ownership of the data.
E	Strategic Vision	Create data products that are reusable
K	Strategic Vision	Data product is something touching the reality, we understand the immediate need and how we can consume, be part of it.
P	Strategic Vision	The key to everything is change management communication and simplification.
A	Sustain acceleration	Some governance processes are standard across all the data product
F	Sustain acceleration	meetings for practical experience sharing initiated by the Data Mesh team.
K	Sustain acceleration	Spread success stories
P	Sustain acceleration	There is a learning curve. Of course, the first data product will take more time but then that lead time is going to become (...)
F	Business-IT Divide	We presented the concept of data product, governance, roles, etc. but it lands pretty difficult as the explanations are still pretty (...)
G	Business-IT Divide	Like Henry Ford, if you ask the customer what he needs, he will answer "a faster horse".
L	Business-IT Divide	When you work on a daily basis you think about your project, not on the big picture, therefore the adaptation is difficult.
C	Complexity of Data Products	The solution is not always what the business wants, but what they need.
M	Complexity of Data Products	A data product can be different things, it is good feedback, but it doesn't help us understand what we should do.
I	Complexity of Data Products	The initial workload is scary, we throw at you this big Excel file with hundreds of lines.
K	Complexity of Data Products	There are two challenges: the data products may or may not need all the data points we have in the domain. And we ask the (...)
E	Organic vs. Structured	We move forward more in an organic way.
F	Organic vs. Structured	We discussed with the Data Mesh team hoping for best practices on how to build data products, but they said it's up to you.
G	Organic vs. Structured	You can't create an architecture that perfectly reflects the organisation chart at time T because in 1 or 2 years maybe the task (...)
K	Organic vs. Structured	Implementing Data Mesh is learning by doing. Not only using the references but also testing what is working for us.
D	Tension in Ownership	IT sells it a bit too easily.
J	Tension in Ownership	Business wants it, but in a silver platter, which is the difficulty for anyone that try to implement it, no matter how user friendly (...)
J	Tension in Ownership	The roles and responsibilities are clear, I just don't think I am that person.
M	Tension in Ownership	Let's imagine I am riding a bike, and you present to me a taxi. I love the idea. But now you give me a car and you tell me to drive it.

Appendix 3 – AI Usage

Throughout the development of this thesis, ChatGPT was used as a writing tool. Its primary function was to improve the clarity, fluency, and structure of self-written content. For instance, sentences or sections initially drafted by the author were reviewed and revised using prompts such as: “Please rewrite this in a more academic tone: {...}”, “How would you say this in English?”, or “Can you make this more concise and fluent?”

In the early phases of the project, ChatGPT also supported the exploratory process. It was used in parallel with traditional academic resources (e.g., university library databases and scholarly search engines) to find a research angle and prompt reflection. Example queries included: “What is underdeveloped in the literature regarding Data Mesh?” or “What are the most widely used change management frameworks?” While not all suggestions were ultimately adopted, these interactions helped sharpen the author’s focus and creative thinking.

During the literature review phase, ChatGPT was occasionally used to explain complex academic papers. When a section of text was conceptually difficult, the model was prompted to paraphrase or summarise its meaning. This allowed for a quicker assessment of a paper’s relevance and supported more efficient navigation of academic sources.

Lastly, at the final stage of the thesis, ChatGPT was used for minor text refinement, such as removing double spaces and verifying that every sentence ended with a period.