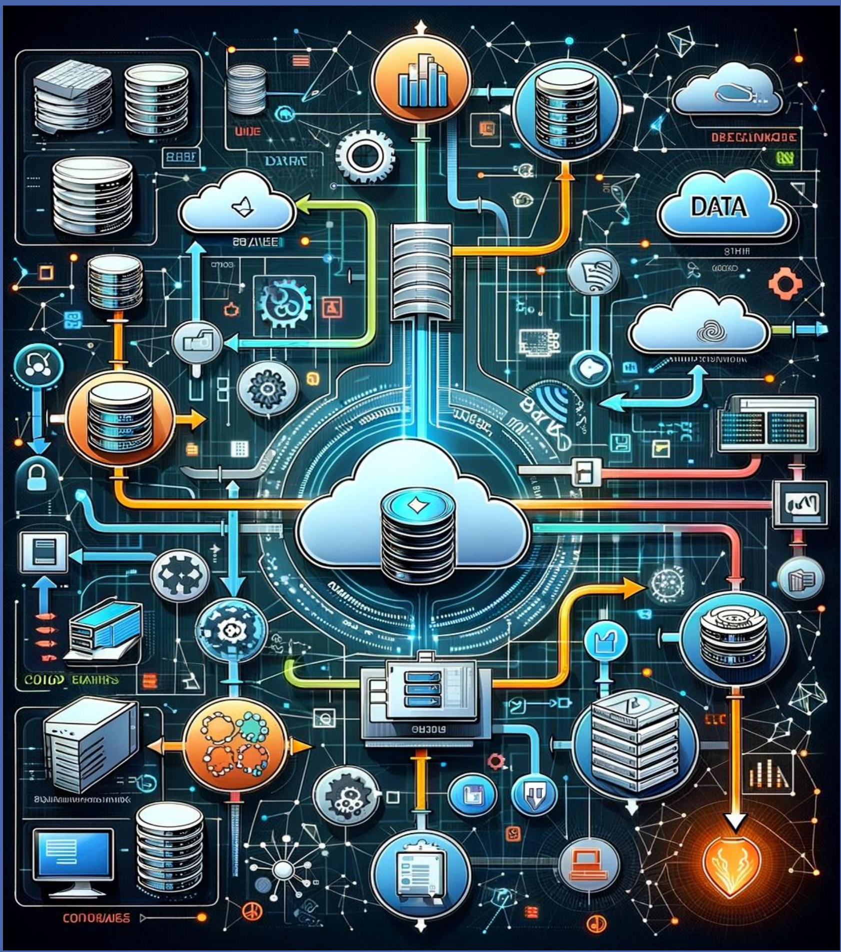

DATA ECOSYSTEMS

Deliverable II:
An overview of data ecosystems, business model components and archetypes

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July 2024

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EXECUTIVE SUMMARY

In today's interconnected world, data has become a critical asset that drives decision-making, innovation, and competitive advantage. The exponential growth of data from diverse sources has transformed it into a fundamental resource akin to oil during the Industrial Revolution. Advanced analytics, AIoT, generative AI, and machine learning enable companies to predict future trends, optimize operations, and make informed decisions, thus enhancing productivity and competitiveness across various sectors. The increasing volume and complexity of data necessitate advanced technologies and sophisticated methods for processing and analysis. Traditional data handling approaches are insufficient, requiring integrated frameworks to fully harness data's potential. The interconnected nature of modern business environments underscores the need for collaborative data ecosystems, where data is shared among stakeholders to drive innovation and operational excellence.

This deliverable aims to bridge the gap between existing knowledge of data ecosystems and the critical insights yet to be uncovered. It explores data ecosystems' definitions, components, value propositions, and business models, providing a comprehensive synthesis of theoretical frameworks and actionable insights. The report is structured into three main parts: defining data ecosystems, understanding value proposition and value capture mechanisms, and developing business model archetypes. The first part of the report defines data ecosystems, identifying four main subsystems: infrastructure, stakeholders, data, and governance. Each subsystem has distinct characteristics and functions, contributing to the overall effectiveness of the ecosystem. The infrastructure subsystem includes the technological backbone necessary for data storage, processing, and transmission. A robust infrastructure supports seamless operations and data accessibility for stakeholders. The stakeholder subsystem comprises human and organizational entities that interact within the ecosystem, fostering data-driven innovation and value creation. The data subsystem involves the flow of information, encompassing data sources, types, and processes for collection, storage, and analysis. The governance subsystem establishes rules, policies, and frameworks for data management, ensuring compliance with regulatory standards and maintaining ecosystem order. Following our aim, we also develop a visual presentation of the components that guide both researchers and practitioners in better understanding this concept.

The second part focuses on the value proposition and value capture mechanisms within data ecosystems, emphasizing the role of AIoT integration. The convergence of Artificial Intelligence and the Internet of Things enhances data ecosystems by enabling real-time data processing and intelligent decision-making. This part explains that understanding value proposition and capture mechanisms in a data ecosystem is critical for organizations aiming to thrive in the data-driven world. A value proposition refers to the unique benefits and advantages that a company promises to deliver to its customers, while capture mechanisms are the strategies and processes used to seize and monetize this value. Organizations that clearly articulate their data value proposition are better positioned to differentiate themselves from competitors, create customer loyalty, and drive revenue growth. This is due to the fact that a well-defined value proposition ensures that data initiatives are closely aligned with business goals, thus enabling more targeted and impactful decision-making. This becomes more critical considering the growing impact and use cases of data as a key resource in various industries. This deliverable emphasizes that effective value capture mechanisms are essential for converting data insights into tangible business outcomes. This involves leveraging advanced technologies such as AIoT to extract actionable insights from vast datasets. By understanding and implementing these mechanisms, practitioners can identify new revenue streams, optimize operations, and enhance customer experiences. The identified value proposition mechanisms include responsive monitoring, object self-service, insight as a service (IaaS), and enhanced user experience. These mechanisms leverage AIoT capabilities to offer unique benefits and innovation opportunities. Key value capture mechanisms include revenue enhancements, cost reduction, monetization enhancement, and sales enhancement. These mechanisms provide businesses with innovative ways to generate revenue, reduce costs, and expand their market presence.

The final part of the report synthesizes previous studies and empirical insights to present practical business model archetypes in AIoT data ecosystems. The identified archetypes include adaptive partnership, user-centric, standardized efficiency, and flexible transaction. The adaptive partnership model features tight control by the provider with high customization for the customer, focusing on personalized, real-time AIoT solutions. The user-centric model emphasizes scalability and market expansion with loose control from the provider and high customization for customers, enhancing customer satisfaction and market reach. The standardized efficiency model involves tight control with limited customization, optimizing resource utilization and operational efficiency. The flexible transaction model adopts a transactional approach with loose control and low customization, focusing on predefined functionalities and new revenue models. Understanding data ecosystems enables companies to streamline operations, reduce costs, and improve productivity through predictive maintenance and supply chain optimization. Analyzing data from various touchpoints allows businesses to tailor their offerings, enhancing customer satisfaction and loyalty. Robust data governance mechanisms ensure data quality, integrity, and security, helping firms avoid legal penalties and build customer trust. The strategic importance of data ecosystems extends to data governance and compliance, emphasizing the need for effective data governance practices.

This deliverable is the second in a series of three tasks within the “embedded AI” project by DIREC. The current report delves into the concept of data ecosystems, elucidating their components, value propositions, and business model configurations. It builds on the theoretical foundations established in the first deliverable, which provided a detailed analysis of existing business models and their evolution, focusing on partner companies such as MAN Energy Solutions, VELUX, and Grundfos. The first deliverable was shared with the project members in June 2023. By defining key concepts and examining the maturity of IoT business models, the first deliverable set the stage for a deeper exploration of how data ecosystems function and create value. The current deliverable synthesizes insights from the first deliverable and expands upon them by exploring the intricacies of data ecosystems and the mechanisms by which they generate and capture value. The findings are crucial for developing scenarios for different business models in AIoT ecosystems, as outlined in the third deliverable. The third deliverable will build upon the insights gained from the current report, focusing on creating new business models that capture the distributed and shared nature of embedded AI technologies. By understanding the foundational elements and strategic implications of data ecosystems, the final deliverable aims to propose innovative business model frameworks or concepts that leverage data and capabilities from digital technologies to ensure robust and adaptive business strategies for the future of actors involved in data ecosystems.

1. INTRODUCTION

In today's interconnected world, data has emerged as a critical asset that drives decision-making, innovation, and competitive advantage. The exponential growth of data from a myriad of sources has transformed it into a fundamental resource for businesses, akin to what oil represented during the Industrial Revolution. Data plays an important role in understanding complex patterns and correlations that are otherwise invisible to the human eye. By utilizing advanced analytics and machine learning, companies can predict future trends with remarkable accuracy, enabling proactive rather than reactive strategies. Data is now the cornerstone for optimizing operations across almost all sectors. It provides granular insights into every facet of a business, from supply chain logistics to customer service interactions. These insights allow businesses to fine-tune their processes, reduce inefficiencies, and improve overall productivity. The ability to make informed decisions based on real-time data empowers organizations to develop strategies that are finely tuned to their unique characteristics, operational requirements, market demands, and consumer preferences. This shift towards data-driven decision-making has elevated data to a critical resource status in almost all industries, from finance and healthcare to retail and manufacturing. The omnipresence of data and its transformative potential underscore its importance, making it indispensable for businesses striving to maintain a competitive edge in an increasingly data-centric world. The proliferation and prevalence of digital technologies have exponentially increased the volume and variety of data available. Such data can originate from a multitude of sources, each offering unique insights into different aspects of business operations.

For example, the Internet of Things (IoT) devices generate vast amounts of data through sensors embedded in physical objects, such as smart home appliances, industrial machinery, and wearable technology. These sensors continuously collect data on various parameters, including temperature, usage patterns, and performance metrics. Production facilities gather data from manufacturing processes, capturing details on production rates, equipment efficiency, and defect rates. This data, when analyzed, provides a granular view of operational performance, and can identify areas for improvement. Generative AI, such as language models and image generation algorithms, creates data by synthesizing new content from existing information. This type of data can come from customer interactions, automated content creation, and virtual simulations, providing businesses with innovative ways to engage customers and develop new products. Embedded AI, integrated directly into hardware devices, allows for real-time data processing and decision-making at the edge. Examples include smart cameras, autonomous vehicles, and intelligent robots, which generate and analyze data locally to optimize performance and enhance functionality. AIoT technologies combine AI with IoT devices, to create systems that can learn from data and make autonomous decisions. These technologies generate data from various sources, such as smart cities, connected healthcare systems, and intelligent supply chains. For instance, AIoT in smart cities collects data from traffic sensors, environmental monitors, and public services, enabling efficient urban planning and resource management. Data from corporate activities, such as financial transactions, human resources, and supply chain operations, provide insights into business performance and operational efficiency. Analyzing this data helps companies identify cost-saving opportunities, improve employee productivity, and optimize logistics. Social data, generated from social media platforms, online reviews, and customer feedback, offers a wealth of information about consumer behavior, preferences, and sentiment. Companies can use social data to gauge public opinion, track brand reputation, and tailor marketing campaigns to target specific demographics. By leveraging these diverse data sources, businesses can comprehensively understand their environment, make more informed decisions, and drive innovation across all aspects of their operations. Data integration and analysis from these various sources enable companies to remain agile, responsive, and competitive in an ever-evolving market landscape.

The impact of data on businesses is profound and multifaceted. Firstly, data-driven insights enable companies to optimize their operations, leading to cost savings and increased efficiency. For instance, in manufacturing, data analytics can predict equipment failures and schedule proactive maintenance, reducing downtime and extending machinery lifespan. Secondly, data empowers companies to enhance customer experiences through personalization. Retailers can analyze purchase histories and browsing behaviors to recommend products tailored to individual preferences, increasing customer satisfaction and loyalty. Furthermore, data informs strategic decisions, such as market entry, product development, and pricing strategies, ensuring that businesses remain competitive and responsive to market changes. Aside from operational and strategic benefits, data plays a crucial role in fostering innovation. By leveraging advanced analytics and machine learning, companies can uncover hidden patterns and insights that drive new product development and business models. Thus, the strategic use of data transforms businesses, enabling them to not only survive but thrive in an increasingly data-driven world.

The prevalence of vast amounts of data and the exponential proliferation of technologies have fundamentally reshaped the business landscape. As organizations continue to generate and collect unprecedented volumes of data, the challenge has shifted from mere accumulation to the effective management and utilization of this data. The sheer scale and complexity of data necessitate advanced technologies and sophisticated methods to process, analyze, and derive actionable insights. Traditional approaches to data handling are no longer sufficient; instead, integrated, and holistic frameworks are required to harness the full potential of data. This paradigm shift underscores the importance of creating environments where data can seamlessly flow and be accessed by various stakeholders to drive innovation and operational excellence. Amidst this backdrop, companies are increasingly recognizing the need to collaborate and cooperate within a broader network. The interconnected nature of today’s business environment means that no organization operates in isolation. By sharing data and resources, companies can leverage each other's strengths, mitigate risks, and capitalize on collective opportunities. Collaborative efforts are particularly crucial in addressing complex challenges that span multiple domains, such as supply chain optimization, customer experience enhancement, and industry-wide compliance with regulations. The ability to integrate data from diverse sources allows for a more comprehensive understanding of issues, fostering a collaborative culture that is essential for sustained progress and innovation. This collaborative approach has led to the formation of new ecosystems that foster data flow and circulation to create value and drive innovation. These data ecosystems are dynamic and adaptive, characterized by the interplay of various entities, including businesses, technology providers, regulatory bodies, and consumers. Within these ecosystems, data is not just an isolated asset but a shared resource that fuels continuous improvement and advancement. The fluid exchange of data enables organizations to stay agile, respond to emerging trends, and co-create solutions that benefit all participants. As a result, data ecosystems have become the backbone of modern business strategies, enabling companies to transform raw data into valuable insights and actionable knowledge, thereby unlocking new possibilities for growth and development.

Data ecosystems are increasingly becoming a vital aspect of modern business operations and strategies. At their core, data ecosystems comprise a network of interconnected data sources, storage solutions, processing tools, analytics platforms, and end-users, all interacting to extract meaningful insights from data. The importance of data ecosystems lies in their ability to facilitate the seamless flow of information across various entities, enabling organizations to harness data's full potential. For companies working with data and data-driven technologies, understanding, and integrating data ecosystems is essential for several compelling reasons. First and foremost, data ecosystems enable informed decision-making. By integrating diverse data sources, companies can gain a holistic view of their operations, market conditions, and customer behaviors. This comprehensive understanding allows businesses to make more accurate and strategic decisions. The ability to make data-driven decisions helps firms stay competitive and responsive to market dynamics. Secondly, data ecosystems provide a significant competitive advantage. In today's fastpaced and highly competitive business environment, companies that can quickly process and analyze data are better positioned to identify opportunities and mitigate risks. A well-developed data ecosystem allows for the rapid extraction of insights, which can inform product development, market entry strategies, and customer engagement initiatives. Moreover, data ecosystems foster innovation and agility. The seamless integration of data from various sources enables companies to experiment with new business models, products, and services. Organizations can use advanced analytics and machine learning to uncover patterns and correlations that would be impossible to detect manually. This capability is particularly crucial in industries such as healthcare, where data-driven insights can lead to breakthroughs in medical research and patient care.

This deliverable is designed to bridge the gap between the existing knowledge of data ecosystems – both from academic literature and practical perspectives – and the critical insights that are yet to be uncovered. As discussed, the advent of vast amounts of data and the proliferation of advanced technologies have fundamentally transformed how businesses operate and collaborate. Despite the significant progress made in understanding data ecosystems, there remains a need for a comprehensive synthesis that combines theoretical frameworks with actionable insights for practitioners. This report aims to fill that void by providing a thorough exploration of data ecosystems, their value propositions, and the business models that can be derived from them. To achieve this, the report addresses three essential questions. First, it seeks to define what a data ecosystem is and delineate its key components. Understanding the foundational elements of data ecosystems is crucial for grasping how they function and the potential they hold for businesses. Second, the report examines the value proposition and value capture mechanisms within these ecosystems. By analyzing how data can create and capture value, companies can better understand the strategic importance of participating in and nurturing their data ecosystems. Finally, the report explores how these mechanisms can be organized to develop robust business model archetypes in these data ecosystems. This involves synthesizing various value propositions and capturing strategies into coherent business models that can guide firms in effectively leveraging their data assets. By addressing these questions, this deliverable aims to provide a comprehensive view that helps organizations navigate the complexities of data ecosystems. It combines theoretical insights with practical applications, offering a roadmap for businesses to harness the power of data in innovative and effective ways. Through this detailed examination, the report not only contributes to the academic discourse but also provides valuable guidance for practitioners seeking to capitalize on the opportunities presented by data ecosystems.

The rest of this document is organized as follows: section two is dedicated to describing data ecosystems and their components. This section takes a general perspective provides an overview of the concept of data ecosystems and describes the components and the subsystems that constitute a data ecosystem. The third section focuses on value proposition and value capture mechanisms in data ecosystems with a focus on AIoT data ecosystems. This section provides a nuanced view of the main components of a business model and paves the way for the final step. In the fourth section, value proposition and value capture mechanisms are merged based on two criteria – customizability and control – to form data ecosystem business model archetypes.

2. WHAT IS A DATA ECOSYSTEM

2.1. DEFINING DATA ECOSYSTEMS

As data has evolved into a pivotal asset and the emphasis on data-driven innovations has intensified, the creation of economic value is increasingly shifting from individual organizations to socio-technical, cross-industry networks known as "data ecosystems" (Gelhaar & Otto, 2020). These ecosystems are characterized and defined differently across various industries, influenced by the stakeholders involved, the technologies employed, and the types of data managed. Terms like big data ecosystems (Li & Liu, 2023; Yunita et al., 2022), open data ecosystems (Feyzbakhsh et al., 2022; Kitsios et al., 2021), IIoT data ecosystems (Khezr et al., 2022), and virtual data ecosystems (Ramalli et al., 2021) reflect these variations. Despite these differences, the essence and overall structure of data ecosystems remain consistent.

At its core, a data ecosystem can be viewed as a network predicated on the sharing of data (Neff et al., 2024). Fundamentally, it is a complex web of actors who utilize and repurpose data for both monetary and non-monetary benefits (D'Hauwers et al., 2022). Stakeholders come together in these ecosystems to achieve a cooperative value proposition that would be unattainable individually (Neff et al., 2024). This collaboration is driven by the goal of co-evolution and the creation and capture of superior value. The co-evolution aspect of data ecosystems involves actors leveraging their collaborative connections and combined capabilities to foster innovation, with the various relationships within the ecosystem contributing to the emergence of roles akin to those found in traditional ecosystems (Neff et al., 2024). Runeson et al. (2021) describe data ecosystems as interconnected networks of stakeholders, including both organizations and individuals, who form relationships based on shared interests. This interconnectedness is supported by an underlying technological infrastructure that facilitates data processing—encompassing discovery, storage, publication, consumption, and reuse—to drive innovation, create value, or sustain new businesses.

While distinct from digital and business ecosystems, data ecosystems share similar characteristics with both. Like digital ecosystems, data ecosystems are open, dynamic, and complex networks of actors, enabled by the modularity of their components and managed without a strict hierarchical order (Jacobides et al., 2018; Neff et al., 2024). Like business ecosystems, the primary objective of a data ecosystem is to develop a central value proposition based on the exchange of data (D'Hauwers et al., 2022). Consequently, data ecosystems facilitate the processes of value creation and capture, offering unprecedented opportunities for stakeholders.

2.2. AIOT AND THE FORMATION OF DATA ECOSYSTEMS

The concept of data ecosystems, characterized by the collaborative and interconnected networks of stakeholders leveraging data to drive innovation and value creation, finds a powerful enabler in the integration of Artificial Intelligence (AI) with the Internet of Things (IoT). AIoT represents the fusion of AI technologies with IoT devices, resulting in a transformative technology that enhances decision-making and expands the capabilities of intelligent applications (Xu et al., 2021). This integration has catalyzed the formation of new data ecosystems that are dynamic, responsive, and capable of generating unprecedented value for businesses. AIoT devices, equipped with sensors and embedded systems, continuously collect, analyze and transmit data. This data is processed and analyzed using advanced AI algorithms, enabling real-time insights and intelligent decision-making (Wang et al., 2021). The advent of AIoT allows for the development of various applications across different environments, utilizing real-world data to enhance functionality and performance (Xu et al., 2021). For instance, in a smart manufacturing setup, AIoT devices can monitor equipment health, predict maintenance needs, and optimize production processes, thereby improving efficiency and reducing downtime. The emergence of AIoT-driven data ecosystems is further bolstered by edge computing, a distributed computing paradigm that processes data at the network's edge, close to where it is generated (Xiao et al., 2019). Edge computing addresses the limitations of bandwidth and privacy concerns associated with centralizing data in the cloud. By enabling local data processing, edge computing ensures real-time, location-aware, and privacy-sensitive services. This decentralized approach aligns with the principles of data ecosystems, where data flows seamlessly across multiple devices and stakeholders, facilitating immediate and actionable insights.

These AIoT-based data ecosystems function by integrating heterogeneous devices with varying computational capabilities, forming a network that supports data collection, processing, and analysis at the edge (Cicirelli et al., 2017). The collaborative nature of these ecosystems allows stakeholders to co-create solutions that address complex urban challenges, leveraging the collective intelligence of the network. The potential opportunities unlocked by AIoT-driven data ecosystems for businesses are vast. In smart agriculture, AIoT devices can monitor soil conditions, weather patterns, and crop health, providing farmers with precise recommendations to optimize yield and reduce resource consumption. In retail, AIoT can enhance inventory management, personalize customer experiences, and streamline supply chains. The healthcare sector can benefit from AIoT through improved patient monitoring, predictive diagnostics, and personalized treatment plans. In manufacturing, AIoT can enhance the production process by integrating intelligent sensors and AI algorithms to monitor machinery and production lines in real time. These systems can predict equipment failures before they occur, schedule maintenance at optimal times to minimize downtime, and optimize production schedules to enhance efficiency. AIoT enables adaptive manufacturing processes that can respond dynamically to changes in demand or supply chain disruptions, ensuring that manufacturing operations remain resilient and agile. By leveraging AIoT, manufacturers can also achieve significant cost savings through reduced waste, improved energy efficiency, and enhanced overall productivity. Moreover, AIoT-driven data ecosystems open new frontiers in the automotive industry, where connected vehicles use AI and IoT to enhance safety, optimize traffic flow, and provide personalized in-car experiences. Autonomous vehicles rely heavily on AIoT to process vast amounts of data from sensors, enabling them to navigate and make decisions in real time. In the energy sector, AIoT facilitates the management of smart grids, optimizing energy distribution and consumption, integrating renewable energy sources more effectively, and reducing operational costs through predictive maintenance of infrastructure.

The adaptability of edge computing to various domains ensures that AIoT-driven data ecosystems can be tailored to meet specific business needs, driving innovation and progress (Sonone et al., 2022). As businesses increasingly rely on real-time data to make informed decisions, the role of AIoT and edge computing in data ecosystems becomes crucial. These technologies not only enhance operational efficiency and decision-making but also create new avenues for value creation and competitive advantage. In summary, the convergence of AI, IoT, and edge computing fosters the development of robust data ecosystems that empower businesses to harness the full potential of their data, paving the way for a more innovative and connected future.

2.3. COMPONENTS OF A DATA ECOSYSTEM

This subsection focuses on the components of a data ecosystem. The views provided in this section are based on a recent study that was presented at the “Academy of Innovation and Entrepreneurship Conference 2024” (ACIEK). This study employs a systematic literature review (SLR) to gather and analyze the existing body of knowledge, aiming to develop a new perspective on the nature of data ecosystems and enhance our understanding of the concept. It contributes to both research and practice by exploring the structure of the data ecosystem and comprehensively mapping its components and offers a thorough perspective on the concept of data ecosystems.

According to the results of our study, a data ecosystem has four constitutive subsystems, and each of these subsystems is made of several components. Each of the main subsystems is distinctive but correlated with unique characteristics and functions. These subsystems include infrastructure, stakeholders, data, and governance. Each subsystem within a data ecosystem possesses distinct characteristics and functions that collectively enhance the ecosystem's overall effectiveness. The infrastructure subsystem forms the technological backbone and encompasses the physical resources necessary for data storage, processing, and transmission. This subsystem ensures that the data ecosystem has a robust and reliable technological foundation. Conversely, the stakeholder’s subsystem comprises the human and organizational entities involved in the ecosystem, such as data users, administrators, and decision-makers. These stakeholders play pivotal roles in shaping the ecosystem's dynamics through their interactions and decisions. The data subsystem is concerned with the information flowing through the ecosystem, including raw data sources, various data types, and the processes of data collection, storage, processing, and analysis. This subsystem is critical for the continuous movement and transformation of data within the ecosystem. Meanwhile, the governance subsystem establishes the rules, policies, and frameworks that regulate interactions and ensure compliance with regulatory standards. Governance defines the power dynamics and operational guidelines, thus maintaining order and accountability within the ecosystem. The effective functioning of the data ecosystem relies on the seamless interaction and collaboration among the infrastructure, stakeholders, data, and governance subsystems. Each subsystem is composed of various components that contribute to its specific functions within the larger ecosystem. These components include specialized software, hardware resources, stakeholder roles, and specific datasets. Understanding the composition and role of each component is crucial, as they are integral to the operations and long-term functionality of the data ecosystem. Each component supports the objectives of its respective subsystem, ensuring that the entire ecosystem operates cohesively and efficiently.

- **The infrastructure subsystem:**

The first subsystem is the infrastructure. This subsystem is extremely important because, technically, all the processes and transactions in a data ecosystem occur within the infrastructure of that ecosystem. It encompasses the factors required to store, archive, or catalog data, as well as the technical architecture to manage it (Šestak & Copot, 2023). Hrustek et al. (2023) regard this subsystem as the backbone of data ecosystems and assert that a sophisticated infrastructure is essential for ensuring the seamless operation of all processes and for creating an accessible environment for the involved stakeholders. The infrastructure supports the operations of the data ecosystem, enabling various stakeholders with different responsibilities to operate, share, and use specific data. To establish a data-driven business capable of acquiring and monetizing valuable data resources, it is imperative to implement an adequate infrastructure (Scheider et al., 2023). A well-developed infrastructure can foundationally support the provision of data to different ecosystem stakeholders (Gupta et al., 2023), which is critical for enabling all the functionalities of the ecosystem. This subsystem includes three components technology, technique, and data spaces.

- **The stakeholder subsystem:**

Participants in an ecosystem are among the most important and influential dimensions, and it is no different in a data ecosystem. The stakeholder subsystem is a critical dimension that consists of the actors that partake in the ecosystem and operate within its boundaries. Beyond pursuing their primary objectives, such as achieving business outcomes or collaborative value creation, ecosystem stakeholders bear the responsibility of fostering and enhancing the growth of the data ecosystem. This is achieved through active engagement, dynamic interaction, supporting data initiatives, and cultivating a culture of data-driven innovation (Hrustek et al., 2023; Runeson et al., 2021). Data ecosystems evolve through the adaptation of stakeholders, their dynamic interactions, feedback loops, and the strengthening of interdependent factors within the ecosystem (Zuiderwijk et al., 2014). Stakeholders contribute to a common goal in the data ecosystem by sharing resources, providing support such as skills and knowledge, offering infrastructure support, creating innovations, and developing new products (Hrustek et al., 2023). This subsystem includes three components, namely, main actors, complementary actors, and third-party actors.

- **The data subsystem:**

Data is the most foundational subsystem because, without data, there is no data ecosystem. Data circulates in the veins of a data ecosystem and ultimately transforms into value for all the stakeholders in various forms. All the fundamental transactions and processes within the data ecosystem are based on and involve data, from its generation and collection to its delivery to the ecosystem's actors (Hrustek et al., 2023). Data holds a central role in the literature on data ecosystems, as it is through data that the discourse on data-centricity and collaborative data sharing begins (Grassi & Lanfranchi, 2022). Contemporary data ecosystems predominantly revolve around the concept of "big data," as evidenced by the current literature (e.g., Bao et al., 2022; Dong et al., 2022; Priestley & Simperl, 2022). The proliferation of generative AI and the Internet of Things (IoT) has significantly contributed to this paradigm shift. The expansive capabilities of generative AI and the ubiquitous presence of IoT devices have led to unprecedented data generation and collection within these ecosystems. Consequently, the data available in today's data ecosystems is characterized by its sheer magnitude, underscoring the importance of big data analytics and management in navigating the complexities of these ecosystems. The data subsystem comprises three components: data source, data properties, and data type.

- **The governance subsystem:**

The last subsystem is data governance, the most studied dimension within the context of the data ecosystem (Runeson et al., 2021). The governance subsystem pertains to the proper management and maintenance of data resources and related activities. It outlines the terms of data use for all stakeholders and delineates their responsibilities (Šestak & Copot, 2023). This subsystem is crucial as it determines the development and progress trajectory of data ecosystem initiatives (Hrustek et al., 2023). Governance mechanisms can also facilitate the emergence of a critical mass of stakeholders, enabling the achievement of system-level benefits (Legenvre & Hameri, 2023). Crucially, data governance addresses who is best positioned to orchestrate data-related initiatives, thus defining the control mechanisms and power structure within the data ecosystem (Legenvre & Hameri, 2023). In the context of the data ecosystem, governance establishes the rules and standards for data management, ensuring compliance with regulatory guidelines, data security, and ethical considerations. It encompasses quality assurance methodologies that involve processes for verifying and maintaining the accuracy, completeness, and reliability of data. By implementing robust data governance practices, ecosystems can ensure that data is used responsibly and effectively, fostering trust among stakeholders and enhancing the overall functionality and value creation within the ecosystem. This governance subsystem is pivotal in guiding the behavior and interactions within the data ecosystem, thereby supporting its sustainable growth and success. This subsystem has three components: general policies, sectoral policies, and power dynamics.

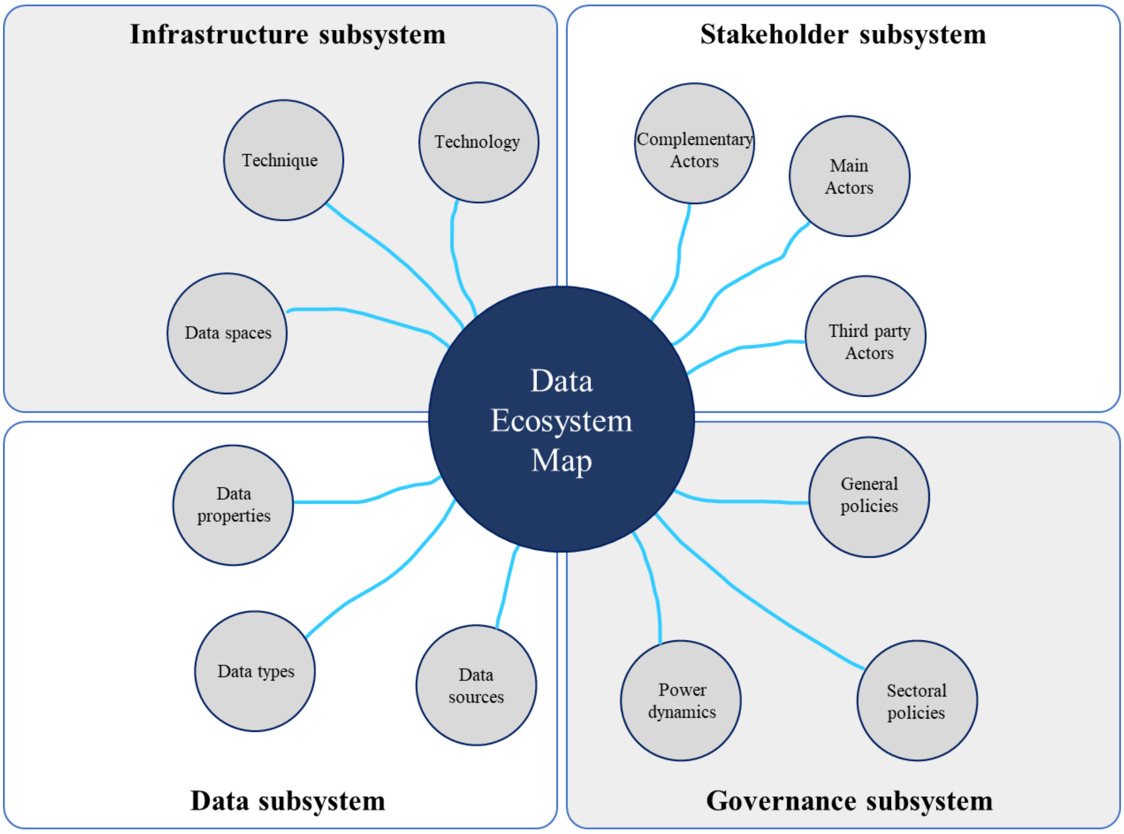

Figure 1, the data ecosystem map

In this section, we delved into the intricacies of data ecosystems by examining their structure, subsystems, and components. Data, often referred to as the new oil or gold in today's business landscape, has become a crucial element in the data-driven economy. This shift has given rise to complex data ecosystems where value is co-created through co-evolution and coopetition. We identified the components and attributes of each subsystem, highlighting their significance for the intricate dynamics and effective functioning of a data ecosystem.

Our analysis revealed the constitutive subsystems and their components. Each subsystem plays a distinctive role and possesses a unique structure, yet they all complement each other and contribute to the overall functionality of the data ecosystem. These subsystems represent layers of the data ecosystem structure that are intricately intertwined and interlinked. The complex relationships and connections between these layers and their components, alongside a wide array of technologies that generate and collect vast amounts of data, form the essence of a complex data ecosystem. The "complex" aspect of the data ecosystem arises from the interconnectedness of these layers and components, as well as the extensive data sets generated and circulated within the system. Our findings also indicate that the complexity of data ecosystems is often linked to the number and diversity of actors, stakeholder relationships, characteristics of data, technology, and infrastructures. Current research highlights those variations in creator type, data scope and format, retention longevity, and access point availability contribute to making the data ecosystem a rich and multifaceted segment of the broader information ecosystem. Furthermore, this study reveals additional factors contributing to this complexity, such as governance approaches, particularly the informal and implicit power dynamics among actors, data sources, and issues related to data ownership and quality. These elements play a crucial role in shaping the intricate nature of data ecosystems and underscore the need for comprehensive management strategies to navigate their complexities effectively.

3. VALUE AND DATA ECOSYSTEMS

Value proposition and capture mechanisms in AIoT data ecosystems

The capability to collect and store ever-growing amounts of data, driven by technological advancements and decreasing costs of computation and storage, has created new business opportunities and transformed operational models for firms (Chen et al., 2012; Mamonov & Triantoro, 2018). Currently, seven of the ten most valuable companies globally employ business models that heavily rely on data to create and capture value. These companies include search-engine giants like Google, social media behemoths like Meta, and hardware producers for data generation and processing like Nvidia and TSMC (CompaniesMarketCap.com, 2023). Similarly, numerous startups are leveraging vast amounts of data to offer innovative solutions, such as large language models like ChatGPT, which aim to replicate human verbal performance (e.g., OpenAI; help.openai.com, 2023). Modern businesses are increasingly advised to incorporate data utilization into their business models, which outline their strategies for creating and capturing economic value (Palmié et al., 2023; Zott et al., 2011). Economic value creation is shifting from being driven by single organizations and traditional value chains to being generated within socio-technical networks known as "data ecosystems" (Gelhaar & Otto, 2020). In today's business environment, participation in these ecosystems is often viewed as essential rather than optional (Gelhaar & Otto, 2020). The dual significance of data and the necessity for collaborative value creation and capture have propelled the formation and prevalence of data ecosystems.

Despite their importance and growing role in the global business landscape, there is a lack of comprehensive understanding of how business models function within data ecosystems. Specifically, there is limited knowledge of value propositions and value capture mechanisms in the complex data ecosystems enabled by recent data-oriented technologies such as the Internet of Things (IoT), generative AI, Artificial Intelligence of Things (AIoT), 5G, and blockchain. From an academic standpoint, existing literature addresses issues related to data ecosystem business models, such as data-ecosystem collaboration for value generation (Kamariotou & Kitsios, 2022), business-model frameworks for ecosystem actors (D'Hauwers et al., 2022), value-creation opportunities for entrepreneurs and firms (Lindman et al., 2016), and business-model transformation (Huhtala et al., 2015). However, it does not adequately explain or conceptualize how companies can propose and capture value within the data-ecosystem context.

The concept of the data ecosystem, both as an academic concept and a real-world phenomenon, has been largely overlooked. While other concepts such as platforms, supply chains, and value chains have been extensively studied and acknowledged for their roles in facilitating value creation and capture (Schreieck et al., 2021; Tan et al., 2020; L. Wang et al., 2019), the nuanced dynamics of data ecosystems remain inadequately explored. This oversight is particularly concerning given the increasing prominence of data ecosystems in the contemporary business landscape. Shifting attention towards data ecosystems is crucial as more companies become data-driven and form various types of data ecosystems to propose and capture value. Ignoring these ecosystems and their underlying aspects limits our ability to fully understand the spectrum of value-creation and value-capture possibilities, as well as the contemporary data-driven phenomena present in these complex data ecosystems.

Given the importance of data and the growing prominence of data ecosystems, it is crucial to delve deeper into the value proposition and value capture mechanisms within these ecosystems. This section focuses on these aspects, aiming to bridge the gap in our current understanding of the issue. Understanding how value is proposed and captured in data ecosystems is essential for both academics and practitioners, as it provides a framework for leveraging data to drive innovation, efficiency, and competitive advantage.

Expanding our understanding of value proposition and value capture mechanisms in data ecosystems is vital because it directly addresses the challenges and opportunities that modern businesses face. As noted earlier, many of the world's leading companies and numerous startups are heavily reliant on data to create and capture value. However, the mechanisms through which this value is realized within the interconnected and dynamic nature of data ecosystems are still not well-defined. By exploring these mechanisms, this section seeks to offer insights that can help organizations strategically navigate and thrive within these complex networks, ultimately contributing to more effective and sustainable data-driven business models.

We focus on value proposition and value capture mechanisms in data ecosystems with a focus on AIoT technology, as it is a crucial enabler that integrates artificial intelligence with the Internet of Things, enhancing real-time data processing and decision-making capabilities. AIoT facilitates the seamless collection, analysis, and utilization of vast amounts of data generated by interconnected devices, leading to more efficient and intelligent systems. This integration enables businesses to unlock new opportunities for innovation, optimize operations, improve customer experiences, and create more robust and adaptive business models. Furthermore, AIoT's ability to provide actionable insights from diverse data sources makes it indispensable for developing sophisticated data ecosystems that drive value creation and capture in the modern digital economy.

3.1. BUSINESS MODELS: VALUE PROPOSITION AND VALUE CAPTURE

A business model delineates the logic behind how a business generates revenue. The concept of a business model has emerged as a crucial framework for describing the interplay between a firm's strategy and its business processes (Böttcher et al., n.d.; Palmié et al., 2023). It comprises four main components: value propositions, which include the core offering and address customers' needs; value creation, which involves transforming resources into value for customers; value delivery, which encompasses the processes for delivering the proposed value to the customer, including the architecture of the value chain, channels of delivery, and collaboration; and value capture, which involves securing value for the firm through its revenue streams and cost structure in exchange for its offerings (Amit & Zott, 2001; Peprah et al., 2022; Zott et al., 2011). Therefore, a business model can be seen as "the logic of the firm, the way it operates, and how it creates value for its stakeholders" (Casadesus-Masanell & Ricart, 2010, p.196). Additionally, a business model explains how a firm commercializes a technology, the benefits it aims to create for its customers, and how it intends to gain from delivering these benefits (Amit & Zott, 2001; Richardson, 2005). The benefits offered to customers constitute the value propositions, while the benefits the firm gains (i.e., revenues minus costs) result from the value-capture mechanisms employed.

Many scholars and practitioners agree on a multi-component conceptualization of business models, with value propositions and value-capture mechanisms being fundamental (Foss & Saebi, 2018; Teece, 2010). The importance of understanding business models goes beyond their prevalence in academic literature or implications for the real-world business landscape. Grasping business models, particularly value proposition and value capture, is critical because it is integral to the firm's existence. Unlike a technology or a theoretical perspective, a business model is not a tool or an option; it is the logic of a company's existence. Every organization, whether commercial or non-commercial, must create some form of value for a target audience and receive some form of (economic) value in return. Thus, business-model theory (Amit & Zott, 2001; Teece, 2010; Zott et al., 2011) has been expanded in various areas, including information systems (IS), explaining firms' value propositions and value capture by considering different aspects of the business model notion alongside the nature of technology as a critical enabler of these business models.

In the context of data ecosystems, value propositions and value capture are intimately tied to data as a critical resource, often referred to as the "new oil" (Rong, 2022) or the "new gold" (Goossens et al., 2015). Inter-organizational cooperation within data ecosystems is fundamentally based on the exchange of data within and across organizational boundaries, where actors collaborate to develop value propositions that they could not achieve individually (Neff et al., 2024). Here, the business model encompasses a system of activities that extend beyond the focal firm, facilitating interactions among ecosystem actors. This activity system serves as a construct for managing environmental dynamism (Böttcher et al., 2022). At the core of the ecosystem lies a cooperative value proposition, with partners, activities, and required alignments specified accordingly (Neff et al., 2024). The literature has also theorized that actors play different roles in the ecosystem's value proposition and are significantly influenced by these propositions (Hillebrand, 2022; McLeod, 2023).

While understanding value propositions in data ecosystems is crucial, equally important is the concept of value capture within these ecosystems. Effective value-capture mechanisms contribute to the overall sustainability and resilience of the ecosystem. These mechanisms drive innovation, experimentation, and adaptation to changing market conditions, encouraging actors to continually explore new opportunities. Additionally, value-capture mechanisms shape the behavior and interactions of ecosystem participants, ensuring alignment with the ecosystem's overarching goals and values. Thus, the significance of value capture extends beyond individual actors to the broader ecosystem. By ensuring the viability and profitability of data-driven initiatives, value-capture mechanisms facilitate ecosystem growth and evolution, attracting new participants and promoting expansion. However, despite the recent focus on data ecosystems, there is still a lack of comprehensive understanding regarding value propositions and value-capture mechanisms within these ecosystems.

Moreover, one of the major drivers behind the implementation of AIoT technology is the development of robust business models, which empower companies to invest, reach new markets, and generate new revenue streams (Bucherer & Uckelmann, 2011; Cranmer et al., 2022). These business models also facilitate the reengineering of business competencies to adapt to changing environments (Haaker et al., 2021). AIoT offers new opportunities for value creation and capture by enhancing capabilities and improving outcomes. Well-structured AIoT business models enable companies to identify novel use cases, address customer needs, and tap into potential market segments that were previously inaccessible. The transformative power of AIoT lies in its ability to generate, collect, and analyze vast amounts of data. By understanding and designing effective business models, organizations can harness this data to create value for relevant users. This data-driven approach allows for the development of customized solutions and tailored offerings, leading to higher customer satisfaction and loyalty. Additionally, it opens new avenues for revenue generation and monetization. Consequently, AIoT not only drives innovation but also supports sustainable business growth by aligning with the evolving needs of customers and markets.

3.2. AIOT: WHEN AI AND IOT CONVERGE

The acceptance and adoption of technology hinge on the benefits it offers to firms and their customers (F. Zhang et al., 2023). AIoT enables the formation of complex data ecosystems, where new value propositions can emerge, and innovative value-capture mechanisms can be leveraged to maximize the benefits of the developed offerings. AIoT refers to the application of AI algorithms to the interconnected smart devices, sensors, and systems of the IoT (Lin et al., 2022). With AIoT, large datasets are generated, collected, and stored via IoT infrastructure and analyzed using deep learning algorithms (Hassan et al., 2020; Shang et al., 2021). AIoT functions like the nervous system of a company's digital structure, with IoT representing the nerves and AI acting as the brain. The integration of AI into IoT infrastructure produces data-driven insights, enables context-aware functionalities, and fosters automation (Duan et al., 2019; Rosendo et al., 2022; J.

Zhang & Tao, 2020). These capabilities facilitate the creation of new value propositions and enhance the overall value delivered to customers and society.

AIoT is intricately linked to the concepts of "edge computing" and "embedded AI" (Narang, 2022; Ogu et al., 2021). Edge computing is a distributed computing paradigm that processes and analyzes data at the edge of the network, close to the data collection devices (Xiao et al., 2019). This approach uses a hierarchy of edge servers with enhanced computational capabilities, eliminating the need to transfer large datasets to a central cloud or fog computing system. Similarly, "embedded AI" involves integrating AI algorithms directly into hardware such as sensors, cameras, or other IoT devices. These devices with embedded AI can generate, process, and analyze data locally without needing a central processing unit, fog computing system, or cloud server. Consequently, edge computing and embedded AI offer a range of location-aware, bandwidth-efficient, real-time, privacy-conscious, and cost-effective services (Baker & Xiang, 2023; Chang et al., 2021; Ogu et al., 2021; J. Zhang & Tao, 2020). Given the capabilities of edge computing and embedded AI, AIoT can drive the development of complex data ecosystems, enabling them to autonomously analyze, learn, and adapt based on collected data. The dynamic interplay among AIoT devices, actors, infrastructure, and data can create feedback loops in which AIoT-driven insights enhance the ecosystem's functionality, leading to new value propositions. Moreover, AIoT-enabled devices and the swift data flow they facilitate support interaction and collaboration among an ecosystem’s actors. This encourages cross-industry partnerships and value co-creation, stimulating the emergence of novel, data-driven business models and innovative value propositions.

Research on AIoT as an enabler of data ecosystems remains limited. Most existing studies focus on technical aspects (Liao et al., 2022; Lin et al., 2022; Xu et al., 2021), with only a few addressing business models (Aliahmadi et al., 2022; Bronner et al., 2021; Hsu et al., 2021). The impact of business models on the value that customers and firms derive from technology can be greater than the impact of the technology itself (Miehé et al., 2023). Therefore, examining how business models and their components, including value propositions and value-capture mechanisms, function is essential for understanding the potential and capabilities of emerging technologies like AIoT and associated data ecosystems. In this paper, we use AIoT as the empirical context for our study of data ecosystems, conducting archival and interview studies to address our research questions.

3.3. METHODS OF RESEARCH

This study aims to explore and delineate the value proposition and value capture mechanisms in data ecosystems through an exploratory qualitative approach. By examining archival data from a selected group of pioneering AIoT companies, we seek to identify the value propositions and mechanisms employed to capture value within these data ecosystems. This foundational understanding is crucial for developing business model archetypes in AIoT data ecosystems, setting the stage for more in-depth analysis and practical application. We employed an exploratory qualitative approach to study the value propositions developed and provided by companies in the AIoT data ecosystem. This approach allows us to investigate business models in their natural settings, revealing underlying or non-obvious aspects that are critical for understanding the nuances of these models. By capturing the current state and generating preliminary theories, this method provides a clear and comprehensive picture of how AIoT companies create and capture value.

To identify the most relevant companies for our study, we utilized purposeful sampling, starting with a list of 78 AIoT companies from Businesswire (2022) and an additional 120 companies from the AIoT Korea Exhibition (2022). Through snowball sampling, we expanded our pool to over 200 companies. We then applied three inclusion/exclusion criteria to refine our selection. First, we excluded companies focused solely on AI or IoT, as our interest lies in the intersection of both technologies. Second, we removed firms that do not actively participate in the data ecosystem. Companies that merely produce and sell AIoT devices or develop software without integrating data ecosystem principles were excluded. We retained firms whose business models revolve around collecting, sharing, analyzing, and monetizing data generated by AIoT. Finally, we included only companies for which we could access sufficient information to analyze their value propositions and value-capture mechanisms. Applying these criteria resulted in a final sample of 28 AIoT companies with 36 distinct data-driven offerings. This curated selection allowed us to delve deeply into the mechanisms these companies use to create and capture value, providing insights that are directly applicable to both academic research and practical implementation in the field of AIoT and data ecosystems.

3.4. VALUE PROPOSITION MECHANISMS:

In exploring the value proposition mechanisms within AIoT-driven data ecosystems, we have identified four primary categories that encapsulate the value proposition mechanisms. These mechanisms include responsive monitoring, object self-service, insight as a service, and enhanced user experience. Each mechanism represents a distinct approach to leveraging AIoT capabilities, offering unique benefits and opportunities for innovation. In the following sections, we will delve into each mechanism, providing insights into their functionality and the ways in which they contribute to the overall value creation within data ecosystems.

Responsive Monitoring: Responsive monitoring extends beyond traditional reactive monitoring by enabling real-time action based on data. This category includes two archetypes: "automatic corrective function" and "predictive maintenance." Automatic corrective function involves AIoT devices continuously collecting and comparing data to desired parameters and initiating actions to correct deviations. For example, NYX's Gosleep app measures sleep factors and adjusts the room's climate through a digitally enhanced HVAC system. Predictive maintenance identifies operational anomalies before failures occur, replacing scheduled maintenance to increase efficiency and reduce costs.

Object Self-Service: this mechanism aims to make objects more autonomous, reducing reliance on human intervention. This category includes "self-adjustment and replenishment" and "self-operation." Self-adjustment and replenishment involve objects adjusting to conditions or reordering consumables as needed, such as smart printers ordering cartridges. Bosch's Networked Home improves security and comfort through smart appliance interactions. Self-operation goes further by enabling objects to operate with minimal human intervention, exemplified by Tesla's self-driving capabilities.

Insight as a Service (IaaS): Insight as a Service leverages the increase in data-generating objects to provide meaningful insights. This category includes "real-time insights" and "collective insights." Real-time insights use AI to analyze raw data and provide immediate feedback, often combined with responsive monitoring. For instance, AirDeep's sensors analyze indoor air quality, detecting abnormalities like smoke. Collective insights offer a deeper analysis over time, such as Bosch's AIoT-based tires that track tire behavior for producers, manufacturers, and users, providing valuable long-term insights.

Enhanced User Experience (EUX): Enhanced user experience focuses on improving product interaction through digital add-ons and customizable interfaces. Digital add-ons allow developers to incorporate appealing features, such as an app that adjusts wake-up times based on sleep phases and simulates sunrise. Customizable interfaces use AIoT to tailor the object's interface to individual users, evolving based on their usage. An example is an oven that adjusts cooking settings according to user preferences, providing a personalized experience. Figure 2 depicts the value proposition mechanisms for the AIoT data ecosystems.

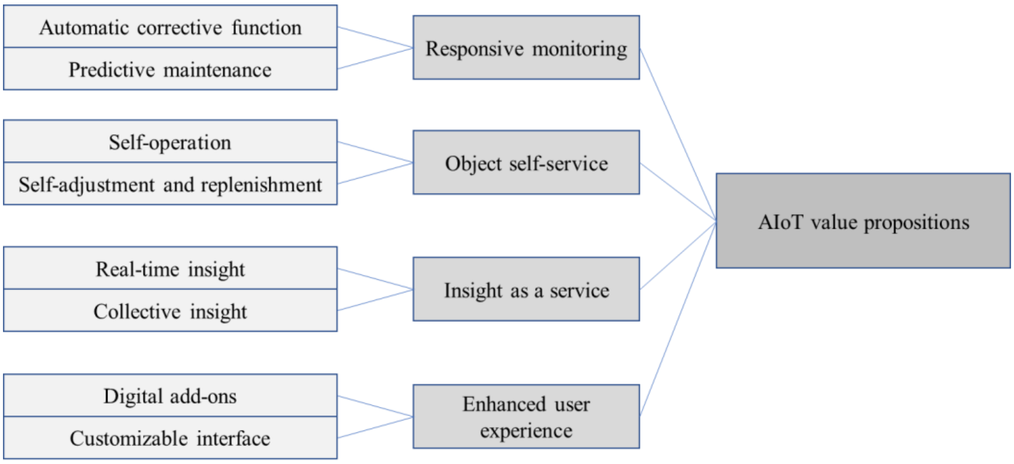

Figure 2, Value proposition mechanisms in AIoT data ecosystems

3.5. VALUE CAPTURE MECHANISMS:

Following our goal to explore data ecosystem business models, we explore the key value capture mechanisms within AIoT-driven data ecosystems, which are crucial for understanding how businesses can effectively monetize AIoT technology. We have identified four primary categories of value capture mechanisms: Revenue Enhancements, Cost Reduction, Monetization Enhancement, and Sales Enhancement. Each mechanism provides a distinct approach to capturing value, offering businesses innovative ways to generate revenue, reduce costs, and expand their market presence. The following sections will delve into each mechanism, providing insights into its implementation and the benefits it brings to AIoT data ecosystems.

Revenue Enhancements: Revenue enhancement involves discovering new revenue sources and developing new revenue models. AIoT supports the creation of new goods and services that can be commercialized, as well as the digital enhancement of existing products, generating new revenue streams. AIoT enables innovative revenue models, such as one-off sales, subscriptions, pay-per-use, and premium upgrades. For instance, Eone's smart-mirror technology "Hey Mirror" transitions from traditional one-off sales to offering recurring services like personalized fitness programs, thereby generating ongoing revenue.

Cost Reduction: Cost reduction focuses on increasing operational efficiency and minimizing data redundancy. AIoT improves efficiency by delivering intelligence directly to where it is needed, allowing data analysis at the edge. This reduces concerns related to cloud computing, such as bandwidth, cost, latency, privacy, and scalability. AIoT's capabilities, such as object or voice recognition, help save energy and time through fault prevention and smart tracking. Additionally, AIoT helps separate useful data from irrelevant data, reducing the costs associated with handling large volumes of unnecessary information.

Monetization Enhancement: Monetization enhancement through segmentation and personalization targets the right customers to maximize revenue. This includes market micro-segmentation, where AIoT divides markets into smaller, more actionable groups based on specific customer needs and preferences, leading to higher satisfaction and revenue. Hyper-personalization further enhances customer experience and willingness to pay by tailoring value propositions to individual preferences. AIoT's real-time insights allow companies to offer bespoke products, driving brand differentiation, customer retention, and repeated purchases.

Sales Enhancement: Sales enhancement involves increasing sales volume through market expansion and business scaling. AIoT enables companies to scale faster and more efficiently by reducing labor requirements and saving energy through automation. This includes "volume scaling" and "market scaling," where companies expand into new geographic areas or untapped domains. For example, an AIoT-based smart-home appliance company can enter the healthcare sector with health monitoring devices. Participation in the AIoT ecosystem opens opportunities for cross-industry solutions, ensuring sustained growth and competitiveness in a dynamic business environment.

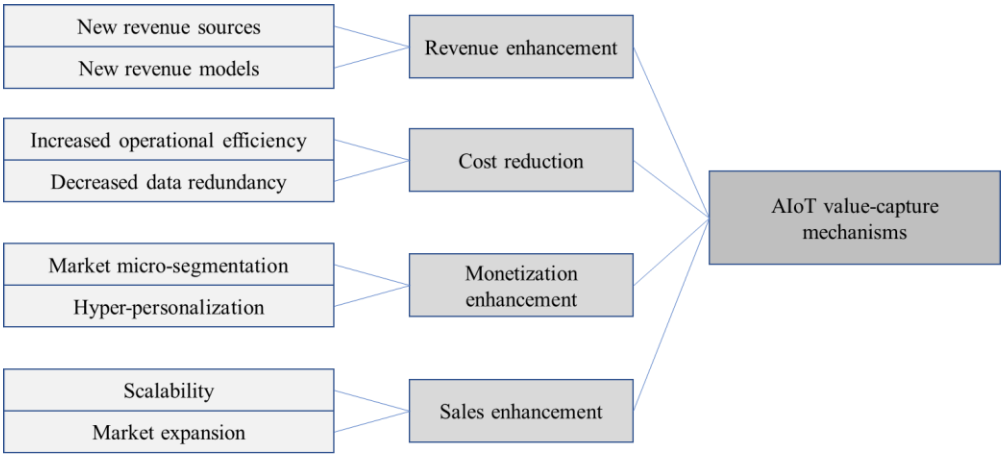

Figure 3, Value capture mechanisms in AIoT data ecosystems

4. BUSINESS MODEL ARCHETYPES

Synthesizing the mechanisms based on control and customization

The previous sections of this deliverable focused on defining the concept of data ecosystems, identifying and describing their main components, and exploring the value proposition and value capture mechanisms within these ecosystems. This foundation has provided a comprehensive understanding of what data ecosystems are and how it is possible to create and capture value within these ecosystems. Building on these insights, this section aims to synthesize the findings from previous studies and introduce new ideas derived from a robust empirical study, ultimately forming business model archetypes that can be realized within these data ecosystems.

To achieve this objective, we will draw on insights from a case study, which utilizes data gathered from interviews with experts. This case study identifies two critical aspects for categorizing the value proposition and value capture mechanisms in AIoT data ecosystems. By integrating these findings with our earlier research, we aim to offer a holistic view of the business model archetypes that are emerging in these technologically advanced environments. The case study in this section focuses on an AIoT data ecosystem centered around a virtual power plant. This data ecosystem comprises various companies, individuals, technologies, and infrastructure, all revolving around the virtual power plant. Essentially, a virtual power plant is a network of decentralized, small-scale power-generating units – such as solar panels, wind turbines, and battery storage systems – that are pooled together to function as a uniform ecosystem. This innovative approach leverages AIoT technologies to optimize energy production and distribution, creating a dynamic and efficient power generation system.

To gain deep insights into this data ecosystem, around 20 in-depth interviews are conducted with a diverse group of experts who have extensive experience and knowledge relevant to this ecosystem. These interviews provided a rich corpus of textual data, totaling more than 270 pages. The depth and granularity of insights obtained from this qualitative inquiry offer a valuable perspective that complements the findings of our earlier studies. This enriched understanding allows us to explore the multifaceted nature of business model archetypes in AIoT data ecosystems more comprehensively. The insights gathered from these interviews help us identify and categorize the value proposition and value capture mechanisms within the virtual power plant ecosystem. By examining these mechanisms in detail, we can derive business model archetypes that are not only theoretical but also grounded in real-world applications. These archetypes illustrate how businesses can leverage AIoT technologies to create innovative solutions and capture value in complex data ecosystems.

This deliverable reports how these mechanisms can be organized to develop robust business model archetypes in these data ecosystems. This involves synthesizing various value propositions and capturing strategies into coherent business models that can guide firms in effectively leveraging their data assets.

4.1. METHODS OF RESEARCH

The methodology of this study followed a structured, step-by-step approach to capture the depth and breadth of insights from the data and address our research questions effectively. We employed a qualitative exploratory case-study approach to empirically examine potential business-model configurations in AIoT data ecosystems (Eisenhardt, 1989). Case studies are particularly suited for in-depth analysis of complex real-life phenomena (Yin, 2003), such as business-model configurations regarding value propositions and value-capture mechanisms. Given the nascent stage of research on data ecosystems and their business models, a thorough initial investigation was necessary to pave the way for future studies and hypotheses. The case-study approach also facilitates triangulation, strengthening the validity of our findings by examining the research topic from multiple perspectives (Oesterreich & Teuteberg, 2016). We utilized both method and data triangulation, combining results from our archival study with insights from our case-study research to enhance our analysis and synthesize our findings more comprehensively. For data collection, we selected an AIoT data ecosystem centered around a virtual power plant (VPP). VPPs use software systems to manage and optimize power generation and storage resources through unified, web-connected platforms (Asmus, 2010). These systems represent an aggregation of diverse, distributed resources across various points within a distribution network (Saboori et al., 2011). VPPs exemplify AIoT data ecosystems as they leverage data from distributed sources, integrate it into centralized systems, analyze it to inform decision-making, and continuously optimize operations using IoT devices, AI algorithms, edge computing, and embedded AI.

The VPP data ecosystems studied were based in Germany and Switzerland, involving companies, individuals, technologies, and infrastructure. Using a purposeful sampling approach (Suri, 2011), we selected a diverse sample of companies representing various roles, sizes, and activities within the VPP data ecosystem. We conducted in-depth interviews with experts who represent 17 organizations involved in the VPP. These interviews were carried out via online video conferencing platforms and telephone calls, providing flexibility and depth for further discussion and exploration of complex issues. Transcriptions of these interviews resulted in over 270 pages of textual data for analysis. For data analysis, we used "template analysis," a type of thematic analysis suitable for organizing and analyzing qualitative data (King, 2012). Template analysis involves constructing a coding template that summarizes thematic patterns identified in the data and arranges them coherently (Brooks & King, 2014). This method is flexible regarding the style and format of the templates, allowing us to develop themes where the data had the highest richness and depth concerning our research questions. By systematically identifying thematic elements and assigning descriptive labels (codes), we created a clear representation of the interrelations among the diverse themes. Following the six steps of template analysis, we systematically organized our data, enabling us to derive meaningful insights and develop a comprehensive understanding of business-model archetypes in AIoT data ecosystems. This structured approach ensured that our findings were robust, grounded in empirical data, and capable of addressing the research questions effectively.

4.2. DIMENSIONS OF THE ARCHETYPES: CONTROL AND CUSTOMIZATION

In this section, we define and explain the themes and dimensions extracted from the data analysis process and elaborate on the business model archetypes derived from these dimensions. Our analysis focuses on two key dimensions: control and customization, which help us understand and categorize the value proposition and value capture mechanisms in AIoT data ecosystems.

Control is a critical factor in business models, as it influences the ability to manage user behavior, consumption, and access to features. This dimension encompasses three themes: orchestration, data flow, and sourcing. Orchestration involves coordinating activities and managing collaboration among ecosystem actors, ensuring efficient data operations. Data flow refers to managing the data generated within the ecosystem, from collection to dissemination, ensuring data security and compliance. Control over data flow is vital for operational efficiency and strategic decision-making. Sourcing involves decisions about insourcing or outsourcing products and services, affecting cost structures, profit margins, and the degree of control over offerings. Effective sourcing strategies can also enhance partnerships and reduce risks.

Customization refers to modifying offerings to meet specific customer needs and is influenced by the business model. This dimension includes themes such as dynamism, prices, and hardware and software adaptation. Dynamism captures the ongoing changes and advancements in technologies and business models, requiring a proactive approach to leverage evolving capabilities. Customizable pricing strategies can enhance customer satisfaction and competitive positioning, with flexible pricing being crucial for market success. Hardware and software adaptation ensures compatibility and optimal performance within the ecosystem, addressing customer-specific needs and facilitating seamless integration. Adaptation requirements vary, with some customers needing major hardware changes and others requiring software tweaks.

The identified dimensions of control and customization are not prescriptive but rather describe a range within which business-model archetypes can emerge. Each dimension encompasses two attributes: tight or loose control, and high or low customization. These attributes represent trade-offs that must be considered when developing and choosing a business model archetype. Based on our analysis, we developed a framework that integrates these dimensions, providing a new perspective on forming business model archetypes in AIoT data ecosystems. This framework, depicted in Figure 4, features four quadrants, each representing a unique combination of business-model elements, offering a basis for further synthesis of our findings and expanding our understanding of business models in AIoT data ecosystems.

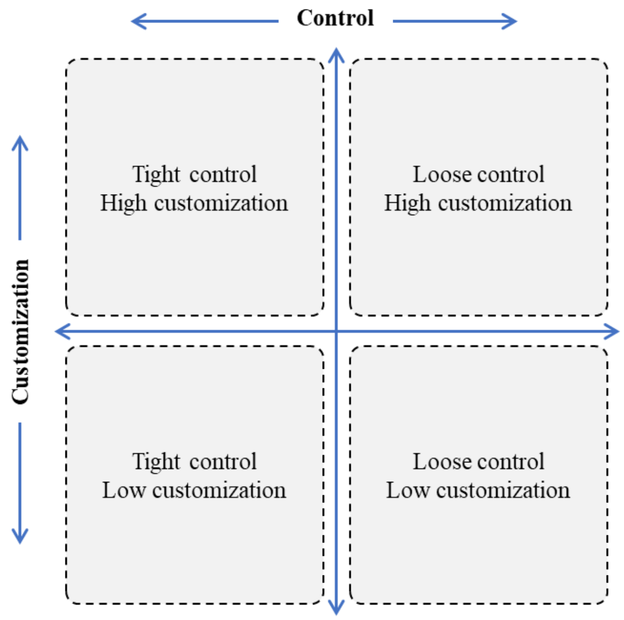

Figure 4, Substructure framework based on control and customization dimensions

4.3. BUSINESS MODEL ARCHETYPES IN AIOT DATA ECOSYSTEMS

This section synthesizes previous studies and new empirical insights to present a practical view of business model archetypes in AIoT data ecosystems. We identified four value propositions and four value-capture mechanisms, which formed the basis for various business model configurations. By analyzing the dimensions of control and customization, we developed a substructure framework that organizes these configurations into distinct archetypes.

Adaptive Partnership: This archetype features tight control by the provider along with high customization for the customer. Providers maintain control over the quality, reliability, and functionality of the offering, while customers can tailor it to their specific needs. The business model includes an Insight as a Service

(IaaS) value proposition, delivering precise, real-time insights. Monetization enhancement through market micro-segmentation and hyper-personalization allow providers to target niche segments and command premium prices, ensuring sustainable and scalable business models.

User-Centric: Characterized by loose control from the provider and high customization for the customer, this archetype focuses on scalability and market expansion. Enhanced user experience is the primary value proposition, offering digital add-ons and customizable interfaces. Sales enhancement as the value-capture mechanism aligns with the provider's goal of penetrating new markets and increasing sales, despite the challenges of decreased control and diverse customer behaviors.

Standardized Efficiency: This archetype involves tight control by the provider and limited customization for customers. The focus is on standardizing processes to optimize resource utilization and streamline operations. The value proposition includes responsive monitoring, such as automatic corrective functions and predictive maintenance. Cost reduction is the key value-capture mechanism, emphasizing increased operational efficiency and decreased data redundancy.

Flexible Transaction: Featuring loose control from the provider and low customization for customers, this archetype adopts a transactional approach. The value proposition is object self-service, allowing for self-adjustment and self-operation. Revenue enhancement is achieved through new revenue sources and models, although this introduces some uncertainty and risk. Customers have limited flexibility, as predefined functionalities dictate the scope of engagement. These business model archetypes provide a framework for understanding how value propositions and value-capture mechanisms can be configured in AIoT data ecosystems, offering a comprehensive view of potential strategies and their implications. Figure 5 depicts our business-model archetype framework for AIoT data ecosystems.

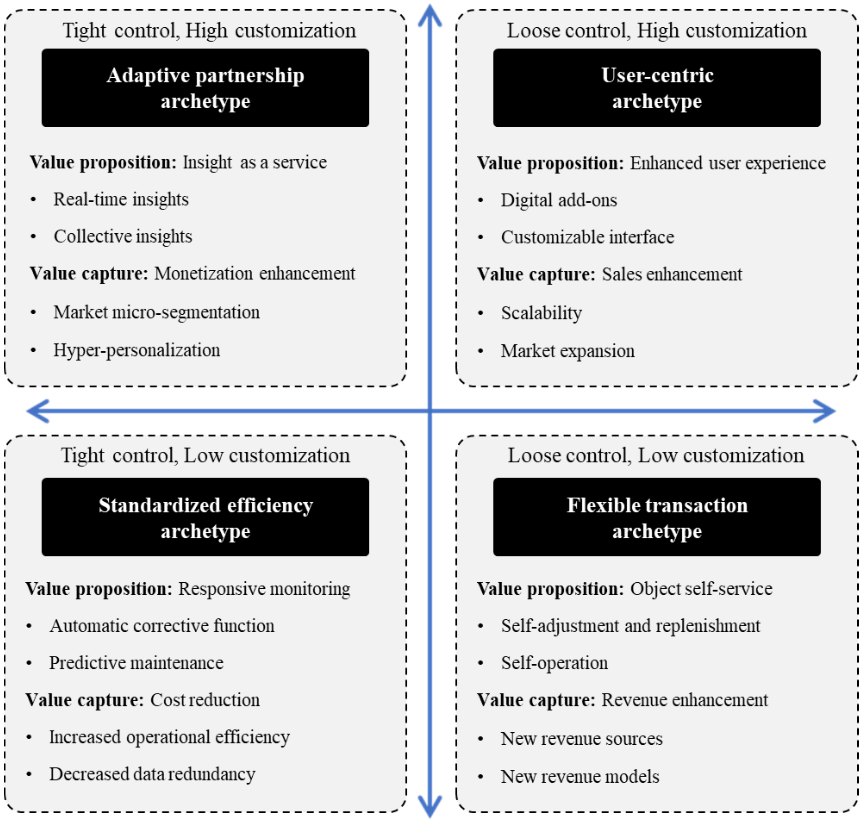

Figure 5, Business-model archetype framework for AIoT data ecosystems.

5. IMPLICATIONS

Implications for practice and contributions to the industry

This section provides an overview of the practical implications and contributions of our studies on data ecosystems, value propositions, value capture mechanisms, and business model archetypes. By integrating insights from our comprehensive research, we aim to provide valuable guidance for professionals and practitioners navigating the complex landscape of AIoT data ecosystems. Our discussion is structured into three key areas: defining data ecosystem components, understanding value propositions and capture mechanisms, and identifying business model archetypes. Each area highlights specific contributions and practical examples to help industry stakeholders apply these insights to their strategic decision-making processes.

5.1. IMPLICATIONS AND CONTRIBUTIONS OF THE FIRST STUDY

The first study delves into the existing literature on data ecosystems, emphasizing the importance of data in modern business operations. It addresses gaps in the current research and provides a detailed view of data ecosystems, highlighting their essential elements and structural complexities. For practitioners, this study offers a comprehensive overview of data ecosystems, making it easier for managers to analyze and understand these systems. This clarity is invaluable for industries like smart manufacturing and energy management, where optimizing data flows and enhancing operational efficiencies are crucial.

Additionally, the study categorizes stakeholders and their roles within data ecosystems, offering deeper insights into effective ecosystem management. By understanding the relationships and governance mechanisms among stakeholders, practitioners can develop strategies to manage these ecosystems more effectively. For example, in smart city projects, where coordination between municipal bodies, technology providers, and citizens is vital, these insights can lead to more successful initiatives. The study emphasizes the importance of robust data governance and stakeholder collaboration, which are critical for designing effective data-sharing policies and fostering trust within the ecosystem.

5.2. IMPLICATIONS AND CONTRIBUTIONS OF THE SECOND STUDY

The second and third studies focus on the interplay between value propositions and value capture mechanisms in AIoT ecosystems, providing practical insights for business leaders. These studies help companies navigate the complexities of creating and capturing value from data, particularly in AIoT-enabled ecosystems. Many firms struggle to find effective business models for these advanced data ecosystems, and our research offers a roadmap by identifying potential business model archetypes.

For example, the "adaptive partnership" model, which combines tight control with high customization, is highly relevant. This model can help businesses form long-term partnerships and increase revenue by offering personalized, real-time AIoT solutions. By focusing on customer-specific needs and providing tailored services, companies can enhance satisfaction and open new revenue streams. This balance between control and customization ensures that providers retain autonomy while meeting evolving customer demands. Practical applications include technology providers working closely with industrial clients to optimize production processes through customized AIoT solutions.

5.3. IMPLICATIONS AND CONTRIBUTIONS OF THE THIRD STUDY

Drawing on insights from the previous studies, this section presents practical business model archetypes for AIoT data ecosystems. These archetypes – Adaptive Partnership, User-Centric, Standardized Efficiency, and Flexible Transaction – offer structured approaches to configuring value propositions and value capture mechanisms. Adaptive Partnership involves providers maintaining tight control over offerings while allowing high customization for customers. This model is ideal for establishing long-term partnerships and driving revenue through personalized services. For instance, renewable energy companies can offer tailored energy management solutions that meet specific customer needs while maintaining control over technology and data. User-centric focuses on scalability and market expansion, with high customization and loose control. This model suits businesses aiming to enter new markets and enhance customer satisfaction. Consumer electronics companies can leverage this archetype to offer customizable smart home devices, increasing market reach and customer engagement. Standardized Efficiency emphasizes tight control and limited customization to optimize resource use and streamline operations. This model benefits industries where standardization is key, such as logistics. Implementing responsive monitoring and predictive maintenance can reduce costs and improve efficiency. Flexible Transaction involves loose control and low customization, focusing on transactional interactions with predefined functionalities. This model suits businesses offering standardized products that require minimal customization, such as utility companies. Adopting new revenue models and diversifying streams can improve financial performance while maintaining simplicity.

Beyond AIoT ecosystems, our research offers broader insights into various data ecosystem contexts. By examining themes like dynamism, data flow, and orchestration, practitioners can make informed strategic decisions and capitalize on emerging trends. Data scientists and analysts can use advanced analytics to tackle business challenges, while data engineers can design scalable systems for seamless data integration and exchange. This research also benefits a wide audience involved in technology-driven business models across industries. Project managers, CEOs, branch managers, and business developers can enhance their understanding of the evolving business landscape. By linking value propositions, value capture strategies, and business model archetypes, practitioners can identify growth strategies and gain competitive advantages in complex data ecosystems.

6. CONCLUSIONS

This report is the second deliverable from a three-part package from CBS in the “embedded AI” project. In this deliverable three main ideas are proposed and discussed. First, we defined the concept of data ecosystems and described its components. Second, we identified and discussed the value proposition and capture mechanisms in the context of data ecosystems, and finally, we developed a framework of business model archetypes in data ecosystems. In this regard, we argued that the data-driven agility afforded by understanding data ecosystems allows firms to quickly pivot and adapt to changing market conditions, ensuring long-term sustainability and growth. Having such an understanding has various advantages. Primarily this understanding can lead to improvements in operational efficiency. By utilizing data collection, processing, and analysis, companies can streamline their operations and reduce costs. For instance, predictive maintenance powered by data analytics can help manufacturing firms monitor equipment health and schedule maintenance before failures occur, minimizing downtime and extending the lifespan of machinery. Similarly, supply chain optimization through data ecosystems can also lead to better inventory management, reduced waste, and improved delivery times. These efficiencies translate into significant cost savings and enhanced productivity. Understanding and accurately utilizing the potentials of data ecosystems enable deeper customer insights and personalization. By analyzing data from various touchpoints, such as online behavior, purchase history, and social media interactions, companies can gain a nuanced understanding of customer preferences and behaviors. This knowledge allows businesses to tailor their marketing efforts, product recommendations, and customer service interactions to meet individual needs. Personalized experiences not only enhance customer satisfaction but also drive higher engagement and loyalty. The strategic importance of data ecosystems extends to data governance and compliance as well. We have also argued that having a robust understanding of data ecosystems entails mechanisms for data governance, ensuring data quality, integrity, and security. Effective data governance practices help firms avoid legal penalties, build trust with customers, and protect their reputations.

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July 2024