IMPROVING CONSUMER-PROVIDER INTERACTION WITH DATA PRODUCTS: INSIGHTS FROM TRADITIONAL INDUSTRIES

Completed Research Paper

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Abstract

Data products have emerged as a scalable approach enabling data and analytics to address evolving business challenges. However, the formation and usage of data products implies significant changes to existing ways of working and requires close collaboration of business (as data consumers) and analytics teams (as data providers). As the interactions between consumers and providers are critical in generating value from data and analytics, a thorough understanding is required on how data products change these interactions. To conceptualize these consumer-provider interactions, we adopt three conceptual lenses prevalent in IS literature – transactional, relational, and processual. Based on multiple case studies with ongoing data product initiatives. we identify five mechanisms that support such interactions: data contracts, data catalogs/marketplaces, data product owner, data product manager, data product lifecycle. Our findings contribute to the discourse on value-co-creation where changing role of consumers blends with supplier capabilities to generate higher value for companies.

Keywords: Data product, Data consumer, Data provider, Value co-creation.

1 Introduction

Enterprises have increasingly adopted analytical practices to extract value from the currently increasing volume of data (Mikalef *et al.*, 2017). This allows them to develop new insights, to optimize their performances, and to improve their business capabilities (Grover *et al.*, 2018). However, central teams have become bottlenecks and cannot cope with the increasing business demand for data and analytics (Dehghani, 2021). Data products have become a popular means of addressing recurring consumer needs for data and analytics. According to recent studies, 40% of Chief Data Officers have adopted data product initiatives (Davenport, Bean and Wang, 2024) to develop, launch, and support data-driven analytics and AI products for employees or customers. Data products are defined as a well-managed artifact that meets key consumer requirements by productizing data into a consumable form (Hasan and Legner, 2023b). Moreover, they not only improve the speed at which insights are delivered but also scale analytics across the firm (Desai, Fountaine and Rowshankish, 2022).

Forming data products involves data providers at the source, a series of transformation processes in the middle, and data consumers at the sink (Schlueter Langdon and Sikora, 2020). Hence, to obtain the desired goals with data products, the data providers and consumers must be in sync regarding their expectations. For instance, providers can augment a sales dataset with retail data, synthetic data and transactional data to meet diverse information requests and create a Sales 360º data product that is reusable for different analytical use cases (Hasan and Legner, 2023a). Using data products to organize enterprise data and analytics demands rethinking the consumer-provider interaction. Such interactions have been studied using a purely economic lens that focuses on monetary exchange (Thomas, Leiponen and Koutroumpis, 2023). In contrast, the reach of a data product approach is much wider, requiring resource orchestration, cooperation between operators in key roles, and alignment with the enterprise strategy (Chen *et al.*, 2022). The potential value creation opportunity for both consumers and providers is enabled by sharing knowledge of respective their requirements and capabilities with each other (Someh *et al.*, 2023). Nevertheless, this obvious but important relationship has only limitedly been investigated from a data product perspective and is, therefore, poorly represented in the IS literature. Hence, to explore this further, we propose the following research question:

RQ: *What mechanisms enable consumer-provider interactions for data products?*

To conceptualize the interaction between consumers and providers, we adopt three conceptual lenses from the IT sourcing literature, which have also been applied in studying data partnerships and data sourcing (Jarvenpaa and Markus, 2020). These are the *transactional* view, *relational* view, and the *processual* view. These lenses offer a framework to dissect the interaction between the business and analytics for further investigation (Hagen and Hess, 2021). To understand how data products change consumer-provider interactions, we leveraged multiple case studies (Yin, 2009) and selected six companies that have launched data product initiatives and deployed successful data products. Based on these empirical insights, we identified five mechanisms that that enable such interactions: data contracts, data catalogs/marketplaces, data product owner, data product manager, data product lifecycle. Our findings contribute to the discourse on value co-creation where the changing role of consumers "from isolated to connected, from unaware to aware, and from passive to active" (Prahalad and Ramaswamy, 2004, p. 1) connects with supplier capabilities to generate higher value for companies.

In the next section, we give background on data products, followed by three emerging perspectives found in the IT literature. We then explain the methodology and research process and give the outcomes of our analysis. We conclude by discussing our findings and limitations, as well as providing a vision for future research.

2 Background

2.1 From use-case centric approaches to data products

With the strategic importance data is gaining (Vial, 2023), the demand for data to meet various consumption needs grows. Consequently, organizations are obliged to shift away from an isolated use-case driven, project-based approach toward sustainably delivering analytics (Desai, Fountaine and Rowshankish, 2022). Such use-case approach is reactive in nature when it comes to fulfilling consumer needs and only work specifically for handful, well-defined requests – posing longer-term challenges of reusability and scalability (Dehghani, 2021). As the congruence between the consumer's and provider's expectations is critical for generating useful insights (Mikalef *et al.*, 2017), data must be industrialized in order to scale analytics and meet novel consumption needs (Schlueter Langdon and Sikora, 2020). This instils a long-term view on the usage and management of data and plays a key role in harmonizing the "technical and business point of view to align short-term targets with long-term planning" (Dinter, 2013, p. 1). In short, we need to depart from the style centered on use-cases, as it focuses on short-term data needs, to embrace a broader view which engages human players in co-creating value from data and analytics (Li and Griffin, 2023).

One possible and increasingly popular approach to address these challenges relates to data products, which are defined as "*managed artifacts that satisfy recurring information needs and create value through transforming and packaging relevant data elements into consumable form" (Hasan and Legner, 2023b, p. 11).* Data products drive the *generification* of data by the providers in anticipation of future potential uses which, in turn, are easily repurposed by the consumers for diverse needs such as curating data or building analytics dashboards (Parmiggiani, Amagyei and Kollerud, 2023). The data product mindset encourages creating and providing data as if it were a physical product which can generate value as consumers interact with it (Wang *et al.*, 1998). One of the key principles underpinning the data product approach is captured in a well-defined production process that "encompasses data suppliers, manufacturers and consumers" (Wang, 1998, p. 4). This implies a standard productization approach that transforms data delivered by providers into usable products for consumers. In other words, the providers identify important business challenges, which they then analyze to identify the data they need to acquire, the process they should apply, the required packaging, and the final product to be delivered (Chen *et al.*, 2022). Data products represent an approach to industrializing data, underpinning a 'factory method' which leverages standardized processes to create, transform, and package data to fulfill multiple user needs in a controlled and cost-effective manner (Schlueter Langdon and Sikora, 2020). Adopting a product lens on data, therefore, enables reusability, lowers ownership costs, and ensures an improved product-market fit (Thomas, Leiponen and Koutroumpis, 2023). However, this approach carries the challenge of having to rethink interactions between the data providers and consumers since the consumer role changes from passive to active in the productization process, while the providers experience constantly evolving technological capabilities.

2.2 Three views on consumer-provider interactions for data products

Although data products are seen as key enablers in organizing large organizations' data and analytics (Davenport and Kudyba, 2016), we lack a thorough understanding of how they change the interactions between business (as data consumers) and the data and analytics teams (as data providers). To address this gap and study these interactions, we use three conceptual lenses presented in IT sourcing literature, which have been applied to investigate, among others, data partnerships and data sourcing (Jarvenpaa and Markus, 2020). The *transactional* view reflects on the exchange between providers and consumers; the *relational* view shows how both groups profit from enhancing their modes of cooperation; and the *processual* view exhibits how they benefit by accomplishing a systematic flow of tasks to fulfill the interaction's goals. The three views are discussed below:

Transactional view: Once productized, providers can exchange data with the end consumers to facilitate mutual gain for both parties. This corresponds with the *transactional* view that highlights the exchanges between two parties (Jarvenpaa and Markus, 2020). Such exchanges are expected to mutually benefit the parties involved, as when consumers get the exact data they want and providers generate an income from their effort invested in creating and providing the data (Jarvenpaa and Markus, 2020). Exchanges rely on implicit or explicit agreements between the providers and consumers (Kotlarsky *et al.*, 2018). In the case of data products, as a specific example, providers offer sensitive data counting on the promise that the users respect the regulations which prohibit sharing it with unauthorized parties. Thereby, providers can ensure data security and consumers can comply with organizational rules.

Relational view: This perspective underscores the establishment of a relationship between the data providers and consumers and stresses the various modes of collaboration which impact how they engage with and support one another (Jarvenpaa and Markus, 2020). Such collaboration can actualize within organizational boundaries or with external partners, mutually improving the relationship of the key players (Jarvenpaa and Markus, 2020). Further, these relationships can be bilateral or multilateral, i.e., many consumers receive data from single providers or multiple providers deliver data to a single consumer (Oshri, Kotlarsky and Willcocks, 2015). As in the transactional perspective, the relational view is present in data product thinking. For instance, Davenport and Kudyba (2016) propose 'market feedback' as one of the steps in building data products, that enables the consumers share new ideas, feedback, and concerns with the providers, to which the providers react in improving the data product. To further foster relationships and improve product development, some have suggested offering consumers the roles of data providers and data analysts to refine their understanding of the other party's challenge (Zhang and Xiao, 2020).

Processual view: This perspective looks more concretely at the sequential, well-defined, and transparent process steps through which consumer-provider interaction materializes. Complementary to the other views, this lens "focuses on the value of entanglement of data and operations on data that could take place at any point, from the source to the final reuse" (Jarvenpaa and Markus, 2020, p. 72). Taking a dedicated process view, this perspective is made up of various systems, people, technologies, and supporting functions collaborating to acquire, transform, and deliver data (Jarvenpaa and Markus, 2020). Similar views are propagated through the data product concept as well. Schlueter Langdon and Sikora

(2020) discuss the data productization journey which consists of well-defined processes to analyze the business problem, to acquire, prepare, and package relevant data into products, and to deploy and maintain them through lifecycle and compliance activities. This indicates that providers follow a series of tasks to merge data and operations so that they can meet consumption needs on the consumer side.

3 Methodology

Considering our research objectives, we opted for multiple case studies (Yin, 2009), a methodology "well-suited to capturing the knowledge of practitioners and developing theories from them" (Benbasat, Goldstein and Mead, 1987, p. 370). This would allow us to gain detailed insight on how consumer-provider interaction materializes in naturalistic settings, thereby answering the 'how' questions (Yin, 2009). The multiple case study approach further allows researchers to ensure validity of their results (Patton, 2014) as well as analytical generalizability (Miles, Huberman and Saldaña, 2014). Eventually, the empirical insights accumulated from diverse cases could enable pattern identification on which to build rigorous theories (Ketokivi and Choi, 2014).

3.1 Research process

We divided the research process into two main phases (Table 1). In the first, exploratory phase, to broaden our understanding of firms' overall data product initiatives and practices, we organized three focus groups with an initial sample of 10 large multinational firms. In the second phase, we undertook multiple case studies. Using purposeful sampling, we selected six companies where we conducted narrower semi-structured interviews with key informants to gain depth and advance our understanding of how data products impact and change the consumer-provider interaction within the respective firms.

	Phase 1: Focus groups	**Phase 2: Semi-structured interviews**
Period	May 2022 – December 2022	January 2023 – October 2023
Objective	Understand the firm's broader data product initiative, the key drivers of the strategy, how data is productized and governed.	Gain in-depth understanding of current data products, the key players involved, the interactions, the challenges, and lessons learnt.
Data collection	With 27 participants from 10 firms, each focus group session lasted about 180 minutes. • Focus group 1 (May 2022) discussed broader motivation, challenges, and drivers of adopting data products. • Focus group 2 (September 2022) discussed the creation, management, and provision of data products. • Focus group 3 (December 2022) discussed roles and responsibilities of key stakeholders on data products and expected changes.	With 12 key informants from 6 firms, we conducted semi-structured interviews to understand the firms' overall data product journey, the approaches established in the process, and how, as a result, data products had impacted the consumer-provider interaction.
Data analysis	Coding the commonalities between the initiatives and identifying common phases in the data productization journey.	Coding of the different approaches used, to identify emerging mechanisms that have enhanced the consumer-provider interaction.
Outcomes	Understand the broader goal of data productization, its journey, and key roles involved.	Identification of five common mechanisms driving the interaction between data providers and consumers across the firms.

Table 1. Research process.

3.2 Focus groups

In the first part of our research process, between May 2022 and December 2022, we organized three focus groups with 27 participants who had actively collaborated in a multi-year research program on data management, and in all represented 10 companies. These participants had significant working experience as data management professionals and had a good overview of the business sides of their organization as well. They represented firms that were exploring the opportunities of data product initiatives. Each session was designed to focus on particular aspects of data products (Table 1). Each session's 180-minutes were structured as follows: during the first 20 minutes every participant briefly shared their area of expertise and main points of the prior session were recapped; the next 100 minutes focused on each company, sharing their insights on the chosen topic; the final 60 minutes included open discussions involving all participants. The focus groups were driven by two researchers who organized the meetings physically as well as through hybrid settings. With the participants' permission, all sessions were recorded and documented. The first meeting deliberated on what had driven the establishment of a data product initiative, as well as what motivated it and which challenges it experienced. This gave us a grasp of the current company status regarding their data product journey and their maturity level in managing data products. Building on this foundation, the second meeting focused on the firm's created data products. This gave us insight into the prevalent consumption patterns, the type of data products being built, and how the resources were orchestrated to achieve the required purpose. The final meeting emphasized organizational aspects, such as roles, responsibilities, and governance related to data products. This helped us uncover emerging data product roles and how they interact, as well as the existing implications and challenges.

Company (Industry, number of employees)	Participant designation and experience (in years)	Data products discussed
Company A (Packaging, ~25,000)	Enterprise Data Governance Manager (30+), Service Delivery Manager (17+)	Account and hierarchy dataset, Business partner dataset, Recommendation engines
Company B (Manufacturing, ~85,000)	Data and Analytics Governance Manager (10+), Digitalization Strategy Manager (10+)	Shop-floor control dataset, Analytical dataset, AI/ML models, HR dashboards
Company C (Telecom, ~100,000)	Head of Data Foundation (24+), Lead Data Architect (30+)	Customer information dataset, Supply chain dashboard, Predictive models
Company D (Food, ~250,000)	Senior Product Manager – Commercial Analytics (16+), Global Data Governance Product Manager (25+)	Commercial data foundation, Consumption analytics, Sales forecasting model
Company E (Pharma, ~90,000)	Operations IT Lead (24+), Senior Data Business Analyst (27+)	Order dataset, Patient records, Material master data, recommendation engines
Company F (Retail, ~500,000)	BI and Data Team Lead (22+), Data and Analytics Consultant (32+)	Exchange rate product, Partner banking data

Table 2. Summary of the case companies.

3.3 Semi-structured interviews

The second phase of the research process involved organizing separate semi-structured interview sessions with selected firms to gain additional details on their data product strategy implementation. Following insights gained from the focus groups, the researchers conducted purposeful sampling and selected only companies that had a currently running data product initiative, formed a well-documented data product creation and delivery process, established key governance elements around data products, and agreed to share details of their data products. Based on these criteria, we discarded four of the initial 10 companies from this phase of the research process, finalizing our sample at six companies (Table 2). Subsequently, we conducted interview sessions of one hour duration with key informants from each of the six firms. These informants all had 5+ years of experience working in the firm, were prominently involved in formulating the enterprise data product initiative and had been actively involved in implementing data products. We used an interview guideline comprising four parts (see Table 3) to grasp, more concretely, the firms' current challenges, to examine currently live data products, possible mechanisms that had been implemented, to gather various implications of the data product initiative, and to recognize the lessons learnt thus far. The interviews were conducted on MS Teams and were recorded with the participants' permission.

Interview areas	Guiding questions
Motivation	• What is the motivation for creating data products? • Which challenges and benefits can be solved with data products?
Definition and categories	• How does your organization define data products? • How do you categorize different data products in your organization? • Can you provide two or three examples per category?
Status and changes	• Where do you stand regarding introducing data product thinking? Have you defined concrete milestones? • How does data product thinking change the way you handle data? • What are the implications (e.g., processes, lifecycles, roles, governance, etc.)?
Lessons learnt	• What lessons have you learned? • What challenges do you encounter or foresee? • What are your future plans regarding data products?

Table 3. Interview guideline.

To analyze the interviews, we first went through all the statements, testimonials, and accounts the participants gave and bundled the relevant empirical evidence together. Next, we coded the data using an open coding approach that allowed us to identify the naturally occurring themes emanating from the evidence (Seidel and Urquhart, 2013). Once all the open codes had been prepared, we grouped the common open codes and applied a second round of coding on them to identify more condensed and emerging categories or, in other words, the axial codes (Seidel and Urquhart, 2013). This allowed us to harmonize our understanding of the empirical data and move toward an initial list of mechanisms that could impact the consumer-provider interaction. Doing so, we identified five axial codes – data contracts, data catalogs and marketplaces, data product owners, data product managers, and data product lifecycles. In a final step, we conducted selective coding (Strauss and Corbin, 1998; Seidel and Urquhart, 2013) where the "categories are organized around central explanatory concepts" (Strauss and Corbin, 1998, p. 161). In our case, these concepts were the three conceptual lenses in the literature – *transactional*, *relational,* and *processual,* as it helps us analyze and describe relevant perspectives of consumer-provider interactions. Therefore, in selective coding, we mapped the axial codes onto these theoretical lenses. For instance, the codes 'data contracts' and 'data catalogs & marketplaces' enabled various monetary and non-monetary exchanges between providers and consumers of data, indicating alignment with the *transactional* view; data product owners and managers ensured harmonized communication and cooperation while representing business and analytics teams respectively, thus mapping onto the *relational* view; the data product lifecycle contained sequential process steps that direct a data product's journey from idea to implementation, thus aligning with the *processual* view. These axial codes, which in fact named the mechanisms, and their mapping onto the conceptual lenses were discussed and refined with the participants. This further confirmed our results. Due to page number limitation, Table 4 summarizes the coding process with one simple example.

Empirical evidence	Open codes	Axial codes	Selective code
"We have promised our consumers almost no data latency, 99% uptime, and 24/7 availability."	Service level agreements	Data contracts	*Transactional* (contracts enable a monetary and non-monetary exchange
"We have an agreement that our consumers will be charged at their cost centers once we have approved the request to use data products."	Exchange between key role players		

"It is not only about what data the provider offered but also about what the consumers can and cannot do with it later."	Terms of use		between two parties)
"The BI team was the SAP BW as well as the analytics platform team. Now it is split into the BI team and an advanced analytics team,"	Separation of responsibilities	Data product owner	*Relational* (assumes separate responsibilities and harmonizes the collaboration with analytics teams by representing the business)
"We are trying to implement a data owner concept as well as domain-oriented ownership. But it could be a challenge as we are clearly split between business and IT, and data ownership sits with business."	Ownership with business teams		
"We have a clearly defined role by having designated an analytics data product owner at the centre of our lifecycle, who takes care of the development of the data product."	Analytics data product owner		

Table 4. Excerpts from the coding process.

4 Five Mechanisms Improving Consumer-Provider Interaction

Relying on our case analysis, we identified five mechanisms that enable the consumer-provider interactions for data products (see Table 5). Although we did not find every mechanism fully developed and present in all five cases, mainly due to different levels of maturity and varying priorities of the data product initiatives, we could observe each mechanism in at least three cases. Moreover, there was also agreement and validation during the discussion with the participants that these mechanisms are relevant elements for managing the consumer-provider interaction.

	Transactional view		**Relational view**		**Processual view**
Mechanisms	**Data contracts**	**Data catalogs and marketplaces**	**Data product owners**	**Data product managers**	**Data product lifecycle**
Company A	Termed as *service level agreements* that promise 100% complete metadata in return for consumers identifying incorrect metadata.	Informatica data catalog to enable a smooth data request and data approval process.	Data owner (consumer)	Data analytics leader (provider)	*No standard lifecycle* Tasks entail assessment, preparation, delivery, feedback.
Company B	Provider responds to API calls in milliseconds in return for consumers using the golden record for their work only.	Data product stored in Developer Portal helping consumers choose from an assortment of APIs to submit requests.	Product owner (consumer)	Analytics product manager (provider)	Design & experiment – Implement – Deploy – Consume & monitor – Retire
Company C	Termed as *service level agreements* that offer data in only three standard formats: raw, standardized, and prepared, in return for consumers not building non-authorized datasets.	*Not available* Enterprise Data Warehouse is used as an alternative to provide consumers access to the data products.	Global data product lead (consumer)	Digital product owner (provider)	– Identify – Qualify – Develop – Monitor – Improve

Company D	Provider offers 99.99% data product uptime in return for consumers limiting their use to only the 30 data products offered.	Microsoft Purview data catalog is used to make data products available. By default, individuals with clearance are granted access	Product owner (consumer)	Product manager (provider)	Ideate – Source data – Develop & test – Deploy – Consume and monitor – Retire
Company E	*Not available* Promise to make all data 80% FAIR in return for consumers helping to identify all available data.	Collibra data catalog used to subscribe to data products and perform checkout for usage.	IT product owner (consumer)	Data product manager (provider)	*No standard lifecycle* Tasks entail assessment, development, deployment, use, monitoring
Company F	Provider offers full automation of the data sourcing tasks from external vendor in return for consumer not sourcing it elsewhere.	IT4You platform to enable 'online shopping' of data products where consumers pay for the product and charge cost centers.	Business consultant (consumer)	Product owner (provider)	*No standard lifecycle* Tasks entail sourcing, transformation, deployment, use, monitoring

Table 5. Detailed implementation of the mechanisms in the case companies.

4.1 Transactional view

The *transactional* view describes the exchange between the data provider and consumer. Such exchange requires a platform enabling the exchange, as well as valid agreements between the providers and consumers – both of which are mechanisms. For instance, providers setup terms and conditions for the usage of data products which then has to be respected by the consumers in order generate the most value. Thereby, providers can ensure smooth data delivery and consumers can comply with organizational rules (Company D, E). Further, these exchanges can entail mandated routine tasks such as request and approval, in which consumers follow standard procedures in lodging requests to obtain a data product, and in return, providers give swift approval, saving time and extra effort on both ends (Company B). All these actions are facilitated through a platform. Interestingly, contrary to existing literature that emphasizes the monetary aspect as a function of exchange between providers and consumers (Jarvenpaa and Markus, 2020), we found only very limited evidence of such monetary exchanges in our cases.

4.1.1 Data contracts

Data contracts appeared as one mechanism facilitating the interaction between consumers and providers. In simple terms, data contracts are an agreement between the producer and consumer of data, which guarantees a certain level of service in order to support value-enabling use across multiple scenarios. For instance, Company C established a data contract between its data providers and consumers. The Lead Data Architect said, "*we promise to offer data in three specific formats – raw, standardized, and prepared. But the consumers are expected not to create duplicates or build it in other formats.*" Also, such contracts can take place between other entities enabling the consumer-provider interactions. For instance, the Data and Analytics Consultant at Company F stated that, "*we also think it might be a good idea to have some sort of contractual agreements, although on a smaller scale, between people at the source, the ones handling the platforms, the individuals analyzing the data, the people ensuring proper governance, and of course the final consumer who uses it.*"

Data contracts capture key metadata vital in using the data product, such as data schema details, output and input ports, update frequency, scope of usage, key roles and contacts, as well as infrastructure details that support the data product delivery. In other words, the contract is an exchange of promises in which the provider guarantees a certain level of service to the consumer and, in turn, the consumer fulfills the usage terms and conditions of the data product. Such agreement fits with the *transactional* view found in the literature, which directs the exchange of reliable data according to the usage agreement to support broader value-generating activities (Jarvenpaa and Markus, 2020). For instance, in Company F's 'Exchange rate product' the provider promises accurate daily updates to currency data from the European Central Bank server in return for consumers not directly sourcing and using the same data from public websites for invoice payments. Additionally, data contracts can be seen as complementary documentation of metadata at the product level in contrast to the granular metadata elements captured at the data level which determine terms, objects, types, structures, or context (Méndez and van Hooland, 2014). Combined, a more comprehensive data product documentation is formed offering clarity on how human, technical and organizational aspects that shape the data products are orchestrated (Chen *et al.*, 2022). This allows the providers to record and exhibit all the tasks they undertake to meet consumer needs, and it allows consumers to use and comply with all the regulations post-delivery.

4.1.2 Data catalogs/marketplaces

Enterprise-wide platforms, such as data catalogs and marketplaces, appear as further mechanisms that play a key role in creating transparency on the data product offerings and facilitating interactions between providers and consumers. The provider must make data products available on an accessible platform to enable end consumer consumption. For instance, Company E has implemented the Collibra data catalog to offer a checkout experience. The Operations IT Lead stated, "*it's very simple … consumers come to the catalog to find the data and digital products on offer, check all the relevant metadata and if they want it, select it in their basket and just checkout.*" For Company A, the data catalog/marketplace plays a much larger role. The Enterprise Data Governance Manager mentioned, "*data catalog and marketplace are critical components of our enterprise data management initiative because we want to establish the data product as a concept in its own right … which, by definition, must clearly indicate the implication for the producer and customer and how they must cooperate.*"

Further, data catalogs and marketplaces support data adherence to the FAIR principles (Labadie *et al.*, 2020), which, in turn, empowers consumers with high quality and well organized data across the enterprise (Dehghani, 2021). The easier it is to acquire data products from the provider, the faster the consumers can drive their use-cases and generate the required value, which positively impacts their interaction. This concept strongly resembles a physical product which the consumer could initially have discovered on a product brochure or in a magazine (functionality similar to a data catalog), which they then access by visiting a nearby supermarket, purchasing, and eventually using the product (functionality similar to a data marketplace). More concretely, these platforms enable providers to share data products which, in turn, facilitates the value-generating tasks to be carried out by the consumer (Chen *et al.*, 2022). Also, such platforms can have varying levels of scope. For instance, Company B has the 'Developers' Portal' where the data product developers directly make the artifact available to the consumers and support them in the initial usage. Additionally, Company F has a 'IT4You' platform which incorporates the different functionalities of a catalog and marketplace and positions it as a one-stop shop where consumers can easily obtain data products by having them charged directly to the company cost centers. Such platform mechanisms enable the exchange of data products prompted by the consumers' request and providers' approval, fashioning a standardized way of interacting and fulfilling their respective goals.

4.2 Relational view

The *relational* view emphasizes the various modes of collaboration between consumers and providers, which could impact the way they engage with and support one another. Such a view, more precisely, supports collaboration and correspondence, which improves how the two parties connect with each other. Such mechanisms can be exemplified by assigning dedicated roles around data products to support the consumers and providers individually (Company D), as well as establishing feedback loops that enable ongoing communication between participants to handle conflict, identify opportunities, and improve data products (Company C).

4.2.1 Data product owner role (consumer side)

Dedicated roles such as data product ownership play a vital role in enhancing the consumer side of the interaction and ensuring that the defined data products align with business objectives. More concretely, the owner's main goal is to ensure proper data product use to drive business processes and enable data-driven decision making. From this perspective, the owner is understood to represent the consumers of the data product. For instance, Company C has established a global data product lead role for that purpose. The Head of Data Foundation said, "*the global data product lead actually stays active in our data product lifecycle phases to regularly communicate the needs, challenges, and expectations of the business colleagues.*" Interestingly, in Company F, business consultants take on this job. The Data and Analytics Consultant reiterated that, "*the consultant team traditionally worked closely with the business and knows their inner working ... making them the best placed to represent the consumer.*"

Fadler and Legner (2021) also express such an understanding, establishing that data product owners "address business needs for data driven by analytics use-cases and ensuring business value of a data product over its lifetime" (p. 8). More precisely, the key responsibilities of the data product owner involve matching the data product ideas with the broader enterprise goals and prioritizing the ideas with the highest fit. In the case of Company C, the global data product lead works with the domain use-case squad and subject matter experts to collect and prioritize business use-cases based on how it fits the enterprise strategy. Further, to ensure that the data products attain the desired business objectives, they propose and monitor key performance indicators that reflect products' progress and success. As such, their tasks and activities related to the ownership role generate value by collaborative work with the consumers (Hart, 2002). Moreover, the data product owner acts as a single authoritative voice harmonizing and representing the consumers' needs, concerns, and feedback to the organization in general and to data providers in particular. This helps avoid isolated data requests from consumers, which providers would meet separately, thus evading the drawbacks of the use-case driven approach (Dehghani, 2021). Company E plans to achieve this by establishing a data office to centralize all the data product roles, such as owners and managers, so that both the business and analytics sides can connect regularly. Furthermore, data product owners enable vital business knowledge sharing with providers which, in turn, offers the provider insight on the inner workings of the business and helps configure their mutual relationship (Someh *et al.*, 2023). Clearly, this ownership mechanism further aligns with the *relational* view as this consumer-centric role improves the mode of communication and manages expectations proactively (Jarvenpaa and Markus, 2020). Interestingly, however, for the same role these titles can differ and be placed in different parts of the organization depending on its data product initiatives. For instance, Company F has business consultants who assume this role whereas for Company A it is the data owner.

4.2.2 Data product manager role (provider side)

Another dedicated role, namely that of data product manager, is a central part of enhancing the provider side of the interaction and orchestrating the different teams involved in building and delivering the data product. The data product manager's key objective is to ensure reliable delivery of data products according to business requirements and quick support if they encounter issues. From this viewpoint, the managers, normally positioned in technical or analytical teams, represent the interests of the providers. As the Senior Product Manager – Commercial Analytics at Company D stated, "*the issue is that the business does not understand that data product challenges go way beyond just data ... so the managers must talk about their situation on a regular basis and be transparent about what can and cannot be done.*" Company B has appointed an analytics product manager for this job. Their Data and Analytics Governance Manager said, "*…if you see our lifecycle, this manager basically sits in the middle, in a sense that they oversee and manage the development tasks and forward those insights to the business on a regular basis.*"

The manager's key responsibilities are to translate business needs obtained from the data product owners and to establish technical requirements that the provider team should develop. Further, the manager must be adept at managing product backlog, involving that consumers regularly improve key functionalities and address changing needs and novel complexities – indicating skills required for agile development (Nerur and Balijepally, 2007). For instance, Company D has established the role of data product manager to oversee a portfolio of 30 data products in their data catalog and collect regular feedback from consumers on access and performance issues. Additionally, the manager oversees the data product lifecycle, manages technical resource allocation, and generates value from the analytical side by working closely with the providers (Hart, 2002). Similar to the data product owner, the manager represents an authoritative voice from the provider side to coherently describe and portray their queries, limitations, and capabilities to the business. To ensure that the communication remains organized, Company A divided their BI department into an analytics and a platform function, and appointed a data analytics leader for the analytics team to represent the providers. In this way, the consumers can gain a clear picture of the analytical functions, helping them to align their expectations. This also enables the providers to avoid the pitfalls of fulfilling isolated requests from consumers, helping them ensure a lean enterprise architecture for faster delivery (Desai, Fountaine and Rowshankish, 2022). This mechanism, quite clearly, also aligns with the *relational* view because such a provider-centric role coherently communicates their capabilities to improve the transparency for the consumers (Jarvenpaa and Markus, 2020).

4.3 Processual view

The *processual* view focuses on a systematic flow of tasks to fulfill the goals of the interaction. This helps the provider to be transparent about the well-documented, organized series of steps implemented to address the consumers' needs. Reciprocally, the consumers are able to follow the tasks that produced the data product for them, which reinforces their trust in the artifact (Company B, C). Together, by going back to the chain of processes, they can work toward identifying the root-causes of various data-related problems. Additionally, the process perspective gives an opportunity to implement and track key performance indicators along the process steps and communicate the status and progress to the other party. From the provider angle, metrics such as quality, cost, and efficiency could be interesting and from the consumer perspective, measures such as user satisfaction and adoption rate could be relevant.

4.3.1 Data product lifecycle

The data product lifecycle is uncovered as another mechanism utilized to improve the consumer-provider interaction. This lifecycle is viewed as an actionable guideline on the selection, creation, and maintenance of data products in enterprises. The main goals can be achieved through a series of phases, each consisting of a string of sequential steps giving regular feedback to ensure delivery of the right data product for consumer needs. For instance, Company C has established a data product lifecycle consisting of three feedback loops connecting consumers to the identification, qualification, and development phases. The Lead Data Architect stated, "*this continuous control of various process steps is critical to maintain transparency between both parties and the feedback loops help us achieve that.*" On the other hand, the Digitalization Strategy Manager at Company B mentioned, "*our data product lifecycle is simple and resembles a typical product management lifecycle … it also makes sense for us because we are a manufacturing company and people love to think from the angle of physical products.*"

Although the data product lifecycle model differs from company to company, we have generalized our findings by mapping similar lifecycle steps together and offering a broader term for the different phases. Each phase contains a series of relevant process steps described as instructions:

- **Ideation and qualification**: review collected data product ideas – refine these ideas – check whether similar data products already exist – assess fit to business – select final data product ideas.
- **Data sourcing**: review data requirements – identify data gaps – acquire data from internal or external sources – measure data quality.

- **Development and testing**: move data to staging area – prepare and transform data – build minimum viable product (MVP) – test, gather and incorporate feedback – build first data product version.
- **Deployment**: document data product – configure governance policies – create data contracts – roll out data product in data catalog/marketplaces – communicate to the consumers.
- **Consumption and monitoring**: monitor usage – collect issues and feedback – improve data product – provide training to consumers – ensure adherence to governance policies.
- **Retirement**: identify data products for retirement – assess risk and impact – archive the data product – conserve lessons learnt – communicate to the consumers.

As a standard approach, the data product lifecycle offers a holistic view of the system, people, and processes involved in creating and managing data products. This end-to-end view establishes transparency between the providers and consumers, addressing the disconnect between them due to having "different organizations with very different goals and operational procedures" (Sahri and Moussa, 2021, p. 1). Interestingly, Company C addresses this disconnect by collecting data product ideas from both the consumers and providers and prioritizing ideas that have significant overlaps. Hence, they cover needs from both sides. Further, as "the current pace of business is too fast" (Davenport and Kudyba, 2016, p. 86), such a lifecycle approach enables consumers and providers to connect and share feedback regularly, thus ensuring a higher product-market fit. As such, this lifecycle mechanism aligns with the *processual* view due to the underlying structured sequence of steps that clearly shows how data has changed between providers and consumers (Jarvenpaa and Markus, 2020). From a practical point of view, processes are collections of tasks that can be concretely tracked using performance metrics to check quality, efficiency, cost, time, and resources (Elrod, Murray and Bande, 2013). Along similar lines, the Head of Data Foundation at Company C stated that, "*we track certain metrics in our lifecycle, such as update frequency of data product, data quality, and user consumption ... allowing us to communicate and show progress throughout the journey.*"

5 Discussion and Contribution

The primary goal of our study is to develop improved understanding of the interaction between the data consumers and data producers in an organization that plays a key role in enhancing value generation from data and analytics. To offer thorough understanding of this interaction, we suggest using prevalent perspectives given in the literature, namely *transactional*, *relational,* and *processual* lenses. Our work, therefore, first contributes to conceptualizing the consumer and provider perspectives underpinned by data products, and second, identifies key mechanisms that facilitate their interaction. This also sheds light on how activities in one of the lenses connect with activities in other lenses. Furthermore, our work show that data products connect both the consumers and providers using a productization approach – mapping the capabilities of the provider (analytics) to the needs of the consumer (business). This mapping demands a continuous flow of information between them, coherent and regulated to avoid requirement gaps, misallocation of resources, and data products poorly aligned with business objectives. Hence, the consumer-provider interaction shifts toward a more proactive mode, underpinned by formal, rapid, and iterative cooperation, which can be facilitated by the different mechanisms we highlight in this paper. Prior studies investigated the theoretical lenses in specific contexts such as data monetization (Thomas, Leiponen and Koutroumpis, 2023) and studied few mechanisms, such as data contracts and data catalogs (Truong *et al.*, 2012; Labadie *et al.*, 2020), as standalone topics. We extend these contributions by adopting the three lenses together to dissect how data products can impact consumer-provider interaction at various levels and the mechanisms that help in facilitating this. We graphically represent this interconnection between the five identified mechanisms in Figure 1.

Furthermore, our findings extend the prior understanding around the mechanisms. With the exception of Truong *et al.* (2012), the mechanism of a data contract has rarely been studied. The authors, however, study this in the context of a pure data exchange in a data-as-a-service setting, which limits the broader possibilities that data contracts can create. We extend this narrow view by linking data contracts to the product-view on data, where the provider and consumer of data exchange agreements, expectations, and artifacts – components that are crucial in any human-to-human interaction within an organizational setting (Cropanzano and Mitchell, 2005). Therefore, we argue that such exchanges can also be of a non-monetary nature, challenging the prevalent position given in the literature that the *transactional* view only refers to an exchange involving monetary value (Jarvenpaa and Markus, 2020). Regarding the relational mechanisms, the literature has only recently highlighted the data product owner's key role as someone accountable for ensuring continuing value from data products for business (Fadler and Legner, 2021). We extend this view, by disclosing the data product manager's role as product-centric and one that orchestrates the development and deployment of data products, thus completing the other half of the interaction. From the *processual* perspective, we introduce the data product lifecycle that goes beyond the temporary, use-case-centric way to deliver analytics. For instance, the lifecycle funnels data product ideas from both parties and aligns them with broader business objectives in the ideation stage, shares constant feedback between the phases to ensure product-market fit. Thus, reusability is enabled in the deployment stage with a well-packaged, governed and easily accessible data product. All these features are key tenets of the product-view on data (Wang *et al.*, 1998). Hence, the processual view operationalizes the product-view on data by offering concrete guidelines on how to transform data into data products in organizations.

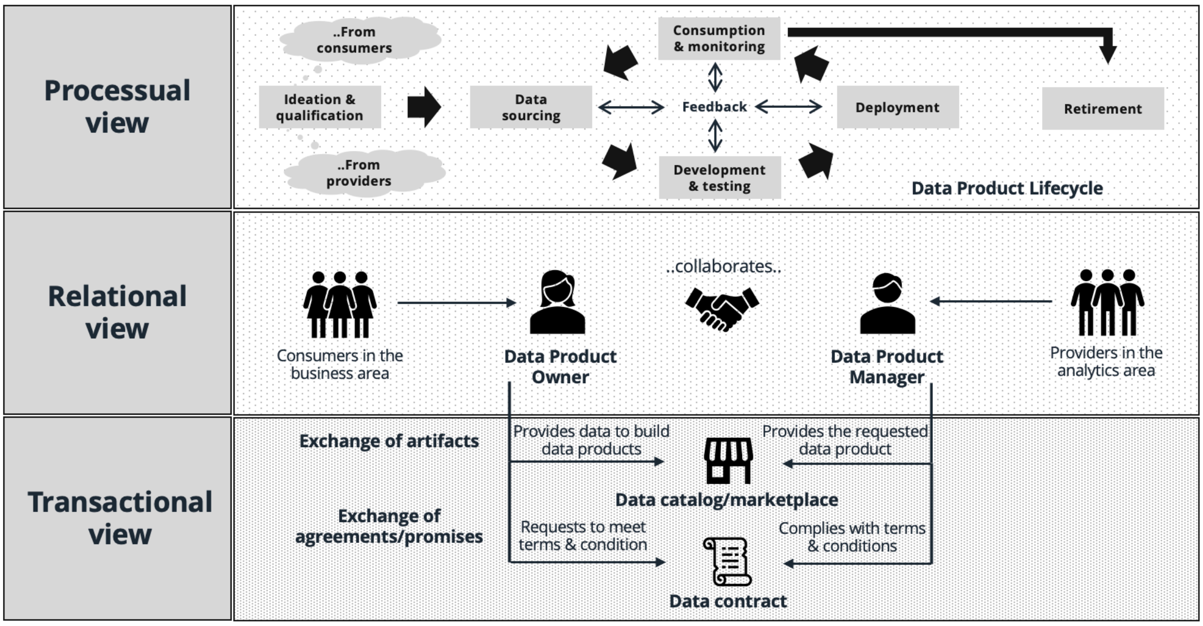

Figure 1. Links between the conceptual lenses in the context of data products.

We further disclose that the dynamics of consumer-provider interaction also depends on the prevalent data management practices within the firm. With the data mesh concept, for instance, many firms have decided to move from a centralized to a decentralized approach with the goal of enhancing data reuse and scale analytics (Machado, Costa and Santos, 2021). Consequently, consumers and providers are re-arranged into different domains, which impacts the way they interact with one another (Dehghani, 2021). This has implications for the different lenses discussed in the paper as well. From the *processual* view, providers in a given domain can now devise their own set of processes to create and manage data products, which may be different to those in the other domains (Wider, Verma and Akhtar, 2023). This might require instituting a clear process management framework at the wider enterprise level to ensure that all the tasks adhere to the broader enterprise regulations (Wider *et al.*, 2023). From a *relational* view, it might require both the data product owners and managers to play a larger role in engaging with counterparts in other domains with identified mechanisms to continuously share information on changing capabilities and expectations on both ends. (Dehghani, 2021). Finally, the *transactional* view might encourage the reformulation of formal sharing agreements due to data product exchange between different domains (Machado, Costa and Santos, 2021). This is because the provider in one domain can now become a consumer in another domain, especially due to the advent of composite data products in which one data product builds on another (Wider, Verma and Akhtar, 2023) – impacting privacy, data protection and compliance topics.

6 Conclusion and Future Research

The interaction between the consumers and providers of data in an organization play a key role in generating value from data and analytics (Dinter, 2013; Mikalef *et al.*, 2018; Li and Griffin, 2023). Our study has analyzed this interaction in the context of data products which have become an important enabler in addressing the increasing demand for data and analytics in a sustainable and scalable manner. We adopt three conceptual lenses – *transactional*, *relational*, and *processual* – prevalent in IT literature, to unpack the data product concept and identify key mechanisms involved in formulating and coordinating the consumer-provider interaction. Based on insights from multiple case studies with ongoing data product initiative, we find five mechanisms enabling the consumer-provider relationship.

Academically, we contribute to the discourse of consumers and producers co-creating value (Prahalad and Ramaswamy, 2004). Building on the predominant view that value co-creation materializes between companies (suppliers) and its clients (customers) (Prahalad and Ramaswamy, 2004), we argue that such value co-creation can also occur internally between providers (suppliers) and consumers (customers) of data products within the confines of a single firm. Therefore, data products can eventually enhance the overall co-creation of non-monetary value, for instance, by improving processes (Desai, Fountaine and Rowshankish, 2022), and monetary value, by packaging and selling data products.

For practitioners, our study offers insights into the mechanisms behind data products that can improve the interaction between the providers and consumers of data. Beyond being useful as an artifact, data products bridge the capability-requirement gap between key stakeholders in the firm, enabling proper coordination in generating value required for the organization. Further, our study establishes concrete mechanisms that can be implemented within companies to help them manage and enhance the relationship between their data providers and consumers.

Our study is not without limitations. Our case companies are all large multinational firms; hence, primarily, our findings might not generalize to digital-native companies. These firms, such as Airbnb and LinkedIn, have already established data products at the heart of their key processes. Traditional firms, however, struggle to understand and adopt data products due to lacking awareness, culture, and dynamicity, while missing out on the crucial value generating opportunities – making our findings very relevant to them. Hence, an avenue for future research could be to comparatively analyze the extent to which these mechanisms are instilled at digital-native firms as opposed to traditional firms.

References

Benbasat, I., Goldstein, D.K. and Mead, M. (1987) 'The Case Research Strategy in Studies of Information Systems', *MIS Quarterly*, 11(3), pp. 369–386.

Chen, P. *et al.* (2022) 'Towards Data Economy: Are Products and Marketplaces Ready?', in *Proceedings of the 48th International Conference on Very Large Data Bases (VLDB)*. Sydney, Australia, pp. 1–4.

Cropanzano, R. and Mitchell, M.S. (2005) 'Social Exchange Theory: An Interdisciplinary Review', *Journal of Management*, 31(6), pp. 874–900. Available at: https://doi.org/10.1177/0149206305279602.

Davenport, T.H., Bean, R. and Wang, R. (2024) *CDO Agenda 2024: Navigating Data and Generative AI Frontiers*. Survey. Amazon Web Services, pp. 1–24.

Davenport, T.H. and Kudyba, S. (2016) 'Designing and Developing Analytics-Based Data Products', *MIT Sloan Management Review*, 58(1), pp. 83–89.

Dehghani, Z. (2021) *Data Mesh - Delivering Data-Driven Value at Scale*. First edition. United Stated of America: O'Reilly Media.

Desai, V., Fountaine, T. and Rowshankish, K. (2022) 'A Better Way to Put Your Data to Work', *Harvard Business Review*, 1 July. Available at: https://hbr.org/2022/07/a-better-way-to-put-your-data-to-work (Accessed: 4 April 2024).

Dinter, B. (2013) 'Success factors for information logistics strategy — An empirical investigation', *Decision Support Systems*, 54(3), pp. 1207–1218. Available at: https://doi.org/10.1016/j.dss.2012.09.001.

Elrod, C., Murray, S. and Bande, S. (2013) 'A Review of Performance Metrics for Supply Chain Management', *Engineering Management Journal*, 25(3), pp. 39–50. Available at: https://doi.org/10.1080/10429247.2013.11431981.

Fadler, M. and Legner, C. (2021) 'Data ownership revisited: clarifying data accountabilities in times of big data and analytics', *Journal of Business Analytics*, 5(1), pp. 123–139.

Grover, V. *et al.* (2018) 'Creating Strategic Business Value from Big Data Analytics: A Research Framework', *Journal of Management Information Systems*, 35(2), pp. 388–423.

Hagen, J. and Hess, T. (2021) 'Collaboration for Big Data Analytics: Investigating the (Troubled) Relationship between Data Science Experts and Functional Managers', in *Proceedings of the 54th Hawaii International Conference on System Sciences*. Hawaii, USA, pp. 1–10.

Hart, D. (2002) 'Ownership as an Issue in Data and Information Sharing: a philosophically based review', *Australasian Journal of Information Systems*, 10(1). Available at: https://doi.org/10.3127/ajis.v10i1.440.

Hasan, M.R. and Legner, C. (2023a) 'Decoding Data Products through the Lens of Work System Theory', in *Proceedings of the Forty-Fourth International Conference on Information Systems (ICIS 2023)*. Hyderabad, India, pp. 1–17.

Hasan, M.R. and Legner, C. (2023b) 'Understanding Data Products: Motivation, Definition, And Categories', in *Proceedings of the Thirty-first European Conference on Information Systems (ECIS 2023)*. Kristiansand, Norway, pp. 1–17.

Jarvenpaa, S.L. and Markus, M.L. (2020) 'Data Sourcing and Data Partnerships: Opportunities for IS Sourcing Research', in *Information Systems Outsourcing*. 5th edn. Springer (Progress in IS), pp. 61–79.

Ketokivi, M. and Choi, T. (2014) 'Renaissance of case research as a scientific method', *Journal of Operations Management*, 32(5), pp. 232–240. Available at: https://doi.org/10.1016/j.jom.2014.03.004.

Kotlarsky, J. *et al.* (2018) *MIS Quarterly Research Curation on IS Sourcing*. Available at: https://www.misqresearchcurations.org/blog/2018/6/26/is-sourcing (Accessed: 14 October 2021).

Labadie, C. *et al.* (2020) 'FAIR Enough? Enhancing the Usage of Enterprise Data with Data Catalogs', in *Proceedings of the 22nd IEEE Conference on Business Informatics (CBI)*. Antwerp, Belgium, pp. 201–210. Available at: https://doi.org/10.1109/CBI49978.2020.00029.

Li, K. and Griffin, M.A. (2023) 'Unpacking human systems in data science innovations: Key innovator perspectives', *Technovation*, 128, pp. 1–12. Available at: https://doi.org/10.1016/j.technovation.2023.102869.

Machado, I., Costa, C. and Santos, M.Y. (2021) 'Data-Driven Information Systems: The Data Mesh Paradigm Shift', in *Proceedings of the 29th International Conference On Information Systems Development*. Valencia, pp. 1–6.

Méndez, E. and van Hooland, S. (2014) 'Metadata Typology and Metadata Uses', in *Handbook of Metadata, Semantics and Ontologies*. World Scientific, pp. 9–39. Available at: https://doi.org/10.1142/9789812836304_0002.

Mikalef, P. *et al.* (2017) 'Big Data Analytics Capability: Antecedents and Business Value', in *Pacific Asia Conference on Information Systems (PACIS 2017)*. Malaysia, pp. 1–14.

Mikalef, P. *et al.* (2018) 'The human side of big data: Understanding the skills of the data scientist in education and industry', in *2018 IEEE Global Engineering Education Conference (EDUCON)*, pp. 503–512. Available at: https://doi.org/10.1109/EDUCON.2018.8363273.

Miles, M.B., Huberman, A.M. and Saldaña, J. (2014) *Qualitative Data Analysis: A Methods Sourcebook*. 3rd edn. SAGE Publications.

Nerur, S. and Balijepally, V. (2007) 'Theoretical reflections on agile development methodologies', *Communications of the ACM*, 50(3), pp. 79–83. Available at: https://doi.org/10.1145/1226736.1226739.

Oshri, I., Kotlarsky, J. and Willcocks, L.P. (2015) *The Handbook of Global Outsourcing and Offshoring*. 3rd edn. London: Palgrave Macmillan.

Parmiggiani, E., Amagyei, N.K. and Kollerud, S.K.S. (2023) 'Data curation as anticipatory generification in data infrastructure', *European Journal of Information Systems*, 0(0), pp. 1–20. Available at: https://doi.org/10.1080/0960085X.2023.2232333.

Patton, M.Q. (2014) *Qualitative Research & Evaluation Methods: Integrating Theory and Practice*. 4th Edition. SAGE Publications.

Prahalad, C.K. and Ramaswamy, V. (2004) 'Co-creating unique value with customers', *Strategy & Leadership*, 32(3), pp. 4–9. Available at: https://doi.org/10.1108/10878570410699249.

Sahri, S. and Moussa, R. (2021) 'Customized Eager-Lazy Data Cleansing for Satisfactory Big Data Veracity', in *25th International Database Engineering & Applications Symposium*. Montreal QC Canada, pp. 157–165. Available at: https://doi.org/10.1145/3472163.3472195.

Schlueter Langdon, C. and Sikora, R. (2020) 'Creating a Data Factory for Data Products', in K.R. Lang et al. (eds) *Smart Business: Technology and Data Enabled Innovative Business Models and Practices*. Cham: Springer International Publishing (Lecture Notes in Business Information Processing), pp. 43–55. Available at: https://doi.org/10.1007/978-3-030-67781-7_5.

Seidel, S. and Urquhart, C. (2013) 'On emergence and forcing in information systems grounded theory studies: the case of Strauss and Corbin', *Journal of Information Technology*, 28(3), pp. 237–260. Available at: https://doi.org/10.1057/jit.2013.17.

Someh, I. *et al.* (2023) 'Configuring Relationships between Analytics and Business Domain Groups for Knowledge Integration', *Journal of the Association for Information Systems*, 24(2), pp. 592–618. Available at: https://doi.org/10.17705/1jais.00782.

Strauss, A.L. and Corbin, J.M. (1998) *Basics of qualitative research: techniques and procedures for developing grounded theory*. 2nd ed. Thousand Oaks: Sage Publications.

Thomas, L.D.W., Leiponen, A. and Koutroumpis, P. (2023) 'Profiting from data products', in *Research Handbook on Digital Strategy*. Edward Elgar Publishing, pp. 255–272. Available at: https://www.elgaronline.com/edcollchap/book/9781800378902/book-part-9781800378902-22.xml (Accessed: 6 November 2023).

Truong, H.-L. *et al.* (2012) 'Data contracts for cloud-based data marketplaces', *International Journal of Computational Science and Engineering*, 7(4), pp. 280–295. Available at: https://doi.org/10.1504/IJCSE.2012.049749.

Vial, G. (2023) 'Data governance and digital innovation: A translational account of practitioner issues for IS research', *Information and Organization*, 33(1), pp. 1–12. Available at: https://doi.org/10.1016/j.infoandorg.2023.100450.

Wang, R.Y. (1998) 'A product perspective on total data quality management', *Communications of the ACM*, 41(2), pp. 58–65. Available at: https://doi.org/10.1145/269012.269022.

Wang, R.Y. *et al.* (1998) 'Manage Your Information as a Product', *MIT Sloan Management Review*, pp. 1–14.

Wider, A., Verma, S. and Akhtar, A. (2023) 'Decentralized Data Governance as Part of a Data Mesh Platform: Concepts and Approaches', in *2023 IEEE International Conference on Web Services (ICWS)*, pp. 746–754. Available at: https://doi.org/10.1109/ICWS60048.2023.00101.

Yin, R.K. (2009) *Case Study Research: Design and Methods*. 4th edn. Thousand Oaks, CA: SAGE Publications.

Zhang, H. and Xiao, Y. (2020) 'Customer involvement in big data analytics and its impact on B2B innovation', *Industrial Marketing Management*, 86, pp. 99–108. Available at: https://doi.org/10.1016/j.indmarman.2019.02.020.