

Schneidmesser, Lea; Butollo, Florian

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Unravelling the Role of Data in Industrial Value Chains

Lea Schneidemesser ^{a,b} and Florian Butollo ^{a,c}

^aWeizenbaum Institute for the Networked Society, Weizenbaum Institute for the Networked Society, Berlin, Germany; ^bUniversity of Erfurt, Thuringia, Germany; ^cTechnical University Berlin, Berlin, Germany

ABSTRACT

This article explores the growing importance of data in global value chains (GVC) and its impact on power relations. We ask (1) how data becomes valuable in GVC, (2) how different types of data are used and (3) how this affects power relations among actors in GVC. We conceptualise data as increasingly important for the development of intangible assets, combining the literatures on intangible assets in GVC and the political economy of data. Based on 88 interviews with practitioners and experts involved in digital business models in Germany, we propose a data typology as an instrument to analyse the effects of data use in GVC based on the origin of data: transactions, product use and processes. We then apply the typology to three case studies of data use in GVC, analysing what kind of intangibles data contribute to and how this leads to upgrading and changes in value chain governance. We argue that data use in industrial value chains does not lead to the concentration of power in the hands of data monopolies. Instead, the creation of value from data rests on a division of labour, with various actors competing for shares of the captured value.

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1. Introduction

Talk of data is everywhere. Data has been dubbed ‘the oil of the twenty-first century’ (The Economist 2017) and ‘the fuel for algorithms’ (Seeberg and Weber 2019). Data is what the ‘fourth industrial revolution’ and its promise of unprecedented productivity hikes rely on. Some see data intelligence as the key to reducing businesses’ environmental impact through better utilisation of capacities, waste reduction and saving of resources (Cool et al. 2024; Mayer-Schönberger and Ramge 2018). Companies strive to create data-based business models to create value in novel ways. Data gathered along supply chains is supposed to improve logistics and procurement and generate greater supply-chain transparency. Data is therefore considered highly valuable (Alaimo, Kallinikos, and Aaltonen 2020, p. 167; Statista 2022; UNCTAD 2021) and organisations feel

CONTACT Lea Schneidemesser  lea.schneidemesser@weizenbaum-institut.de  Weizenbaum-Institut
e. V. Hardenbergstraße 32, Berlin 10623, Germany

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compelled to collect as much data as possible, adhering to the ‘data imperative’ (Fourcade and Healy 2016, p. 8).¹

The intensification of data collection and use has sparked a debate in the social sciences about how the production, capture, analysis and use of data alters hierarchies and power dynamics in the global economy and in specific sectors. This debate was triggered by the rapid growth of the large American tech companies (Google, Amazon, Facebook, Apple and Microsoft = GAFAM) in recent decades and subsequently, their Chinese counterparts (Baidu, Alibaba, Tencent, Huawei = BATH). These companies are considered to be powerful precisely because of their capacity to gather, analyse and valorise data (Rikap 2021; Srnicek 2017; Staab 2024; Zuboff 2019).

Such contributions paved the way for an understanding of what is new and peculiar about the digital economy. Indeed, the relationship between data, software and economic value has been transformed decisively with the rise of the internet and tech companies that engage in immaterial value creation and capture (Kenney and Zysman 2019; Ziegler 2020). However, debates about data that focus on the political economy often lack a more precise and nuanced understanding of how and what type of data is captured and valorised beyond the consumer-facing internet. In these debates, there is a lack of a perspective on how power relations in traditional industries are affected. Accordingly, theoretical instruments for the analysis of power shifts within global value chains (GVC) that go beyond discussing the role of big tech have yet to be developed. Our contribution aims at developing better tools to understand the precise impact of datafication on traditional economic sectors. To this end, it is necessary to unpack *what* data matters *where* and *how* and *under what conditions* data use leads to power concentration in value chains. To do so, we propose linking concepts of intangible assets in GVC research with insights on the political economy of data. This perspective overcomes the big-tech-centeredness of critical political economy and integrates data into the debate about power and knowledge in GVC.

To analyse the impact of datafication on traditional economic sectors we combine an analysis of the use of data by firms with an exploration of the functional division of labour and changing power relations in this process. We ask the following research questions:

- (1) How does data become a valuable asset?
- (2) What different types of data are used?
- (3) How does the use of data affect power relations among actors in GVC?

To answer these questions, we integrate in section Two the literature on intangibles in GVC theory and the political economy of data, thereby outlining the cornerstones for a theory of data in global value chains. In the third section, we lay out our methodology for deriving the empirical findings presented in the subsequent sections. Section Four presents a data typology as an instrument for the differentiation of data types and their contribution to intangible assets. Section Five includes three empirical case studies of data use in value chains in which we highlight divergences in knowledge

¹The belief in a productivity boost through data use by companies dominates the debate about data. However, there is also a vast critical literature that challenges the common notion that the use of data will have a positive economic impact. Critics point to the resource consumption and negative environmental impact of the expanding data economy (Lucivero 2020; Maxwell and Miller 2012; Mytton 2021; Siddik, Shehabi, and Marston 2021) and negative implications of digitalisation and data use for employees and organisational processes (Trittin-Ulbrich et al. 2021).

monopolisation and value distribution due to the use of specific types of data and differences in the production process of intangibles. We then condense our findings into a nuanced understanding of value creation from data and its unique effects on up- or downgrading for certain actors and governance structures in GVC.

2. Cornerstones for a Theory of Data in Global Value Chains

While data constitutes the core of the business models of tech companies, a hybridisation can be observed in industries that traditionally do not revolve around data. In these industries, data-based processes complement the physical manufacturing processes as an increasingly sophisticated layer of organisational activity. At the current stage of manufacturing digitalisation, processes that require data from transactions, processes and products become relevant at specific nodes of inter-firm relationships and in certain activities in value chains. Some examples of these nodes include predictive maintenance of production equipment, procurement of components on B2B e-commerce market-places and data-based staff planning.

To develop a concept of data in value chains, we first need to understand at which points in value chains data becomes relevant. To locate these points, we refer to the discussion on intangible assets; which lies at the core of theory building on global value chains (Durand and Milberg 2020; Kaplinsky 2020; Mudambi 2008). The GVC perspective allows for a fine-grained analysis of the structures and dynamics in inter-firm relationships and focuses on the sequences of value added in an industry, from development to production and product or service use (Gereffi and Fernandez-Stark 2016). This perspective tends to see the complexity of power relations among economic actors more clearly than a political economy perspective that focuses on macro trends. However, research on the role of data in inter-firm relations in GVC is still in its infancy (Andreoni and Roberts 2022; Butollo et al. 2022; Foster and Graham 2017; Sturgeon 2021). We first review the existing insights on intangibles in GVC theory (section 2.1.), before specifying the relationship between intangibles and data (section 2.2.). We interpret data as an increasingly important contribution to the *creation* of intangible assets.

2.1. Intangible Assets in GVC Analysis

The term ‘intangibles’ refers to intellectual or knowledge assets (Lev 2001). These include innovative properties such as R&D, copyright licenses, economic competencies and assets such as brands, marketing, company-specific human capital and organisational structures, as well as computerised information such as software and databases (Corrado, Haltiwanger, and Sichel 2005). The question of whether or not a company can develop intangibles touches a great variety of factors, including the general characteristics of a national, regional or local innovation system, the company’s capabilities to innovate, the conditions for technology transfer, the availability of a suitably trained workforce and the specific corporate cultures. While some of these factors rely on the general institutional and political context in which GVC are embedded and some remain the domain of lab-level research, others rest on the recursiveness gained through feedback loops within the value chain that allow for an incremental improvement of products and processes (Herrigel and Zeitlin 2010). Such incremental

innovations rely on information flows that connect product developers and product users (product innovation) or exist between process monitoring and production process organisation (process innovation).

Since the early 2000s, intangible assets have made up a growing share of the value of final goods (Chen, Los, and Timmer 2021) and generated an increasing share of returns (Alsamawi et al. 2020; Mudambi 2008), despite some inherent problems regarding their monetarisation. The measurable impact of intangibles only partially represents its *de-facto* economic impact; in a knowledge-intensive ‘capitalism without capital’ (Haskel and Westlake 2018), the generation of rents through the capture and monetarisation of intangibles plays an ever more prominent role. Crucially, intangibles are allocated unevenly in disintegrated value chains. Intangible assets tend to be concentrated in activities that are allocated prior to or after the actual manufacturing process; in R&D or design activities on the one hand and in marketing, advertising and after-sales services on the other (Gereffi and Fernandez-Stark 2016; Mudambi 2008). This polarisation is often explained with reference to Vernon’s product life cycle model — pure-play manufacturing activities can easily be replicated. They become commoditised; easily sourced from competing suppliers in off-the-shelf transactions, and hence exposed to high price pressures. Pre- and post-production activities, on the contrary, are more difficult to copy and often include a service dimension customised to users’ preferences (Kaplinsky 2020; Mudambi 2008). While empirical studies on some industries have confirmed this pattern (e.g., Ali-Yrkkö et al. 2011; Chen, Los, and Timmer 2021; Timmer et al. 2014), the equation of low-value-added activities with manufacturing is an over-simplification. Especially in innovation-intensive producer-driven value chains (Gereffi 1994), value creation also rests on manufacturing knowhow that is required to permanently adjust processes, ensure the manufacturability of products and engage in recursive innovation processes that are related to practical shop floor knowledge (Herrigel and Zeitlin 2010; Nahm and Steinfeld 2014). Some intangibles are entangled with and sourced from manufacturing activities.

GVC theory incorporates insights on the role of intangibles in value capture by recording and theorising an uneven distribution of high value-added tasks in geographically fragmented production networks. In the 1990s, Gereffi (1994) identified a new mode of value chain governance — a new structure of control and coordination; buyer-driven commodity chains almost exclusively rely on the control of intangibles by large retailers that coordinate innovation and marketing activities. These outsource most manufacturing activities to companies in developing countries, which — at least in the initial stages of manufacturing offshoring — remain limited to low-value-added manufacturing activities. To escape the commoditisation trap, developing country firms need to reposition themselves in the value chain and engage in economic upgrading by acquiring additional capabilities to improve products, processes, the variety of functions or management capabilities (Bair et al. 2008, p. 28; Humphrey and Schmitz 2002).

While some of these capabilities require genuinely tangible investments in production equipment, they significantly concern intangible aspects related to innovation processes, organisational routines and know-how. Catch-up processes in developing countries simultaneously enhance the pressures on advanced companies to spur innovation so as not to be subjected to downward cost pressures (Mudambi 2008). Even in sophisticated industries such as mechanical engineering or the automotive industry, the threat of commodification currently drives efforts by leading manufacturers to attach digital services (such as

predictive maintenance, data analytics or pay-per-use revenue models) to their products (Krzywdzinski and Butollo 2022; Ziegler 2020; Zysman et al., 2011).

Developing knowledge assets or intangibles therefore touches on two core dynamics in global value chains: economic upgrading and value chain governance. The development of new knowledge assets is often a precondition for economic actors to move towards higher value-added activities that increase efficiency or product quality, such as developing brands or efficient organisational and production processes. The distribution of intangible assets also has implications for the governance of a value chain, defined as the power relationship between chain participants and the resulting division of tasks, costs and profits (Bair et al. 2008, p. 26) — ‘intangibles are essential in manipulating principal power dimensions in GVCs’ (Tups and Dannenberg 2023, p. 777).

Intangible assets and their interlinkage with core categories in GVC theory that define the distribution of power — economic upgrading and governance — are the first conceptual foundation for this paper. The next section discusses the second conceptual building block — the relationship between intangibles and data.

2.2. Data's Contribution to Intangible Assets

The close relationship between data and knowledge and the use of data for economic purposes is not new (Rowley 2007), having existed since long before the development of the internet (Alaimo and Kallinikos 2022, pp. 21–22). It can be seen in bookkeeping techniques developed at the end of the fifteenth century to record transactions (Brockhoff 2022, pp. 26–29), Taylorist scientific management and Lean Production models to rationalise production processes (Womack, Jones, and Roos 1990) and product development informed by consumer preferences and product use (Pfeiffer 2021, pp. 162–165). The history of economic and industrial organisation revolves around the question of how to make use of data derived from manufacturing and business processes, the economy and markets (Baukrowitz et al. 2006, pp. 22–24).

However, data has gained in importance at this current stage of economic development (Kitchin 2022) due to the *digitalisation of data* and new possibilities for data storage, integration and analysis; ‘differently from paper-based records that remain fixed in their support, digital data are editable, constantly updatable, portable, and refigurable’ (Alaimo and Kallinikos 2022, p. 25). While the internet initially mainly processed economic transactions and communication (Baukrowitz et al. 2006, p. 25), the technological progress and integration between hardware and computing led to the digital reproduction of more and more physical processes (Faroukhi et al. 2020, p. 16) in cyber-physical systems so that ‘in the digital economy, flows between firms, resources, or activities are increasingly cast in the medium of digital data’ (Alaimo, Kallinikos, and Aaltonen 2020, p. 174) and shape inter-firm relationships. In the GVC literature, the increasingly prominent role of data — especially for the development of knowledge assets — has only been addressed sporadically and without further conceptualisation. However, in an early suggestion for conceptualising GVC, Michael Porter and Victor Millar named data as an important element of intangibles.

Every value activity has both a physical and an information-processing component. The physical component includes all the physical tasks required to perform the activity. The

information-processing component encompasses the steps required to capture, manipulate, and channel the data necessary to perform the activity. (Porter and Millar 1985)

Other commonly used definitions of intangibles feature data prominently, naming computerised information such as software and databases as one of three types of intangible assets (Corrado, Haltiwanger, and Sichel 2005). This has been taken up more recently by Durand and Milberg (2020) who argue that the modern ‘information economy’ with ‘massive reduction of computation, communication and data storage costs’ (Durand and Milberg 2020, p. 406) is a defining factor for the changing conditions in the production of intangibles in GVC and their ubiquity. The relationship between digitalisation and GVC is also gaining more attention, with efforts to update the initial frameworks to take account of new economic dynamics (Butollo et al. 2022).

When looking at the political economy debate on data through a GVC lens, it becomes apparent that the dominant strand of literature on the political economy of data identifies a form of value chain governance that concentrates power in the hands of the lead firms of the digital economy: the large American and Chinese tech companies. In this process, data is understood as playing a central role in establishing the lead-firm position of tech companies (Rikap 2021; Srnicek 2017; Staab 2024; Tarnoff 2022; Zuboff 2019 and others). This has implications far beyond the monopolisation of economic power in the hands of a few large companies. As authors from anthropology and science and technology studies point out, data is never neutral or objective and subject to interpretation, tech companies that have controlling power over large amounts of data also shape the meaning of data (D’Ignazio and Klein 2020; Gitelman 2013; Kitchin 2022), the design of algorithms (Noble 2018) and infrastructures (Kitchin 2022). Data, in turn, shapes how we understand the world; ‘data do not simply and imperfectly reflect the world, but they also do work in the world and create social realities. They are both a product of action and a product that acts’ (Kitchin 2022, p. 17).

The central role of data in establishing the power position of big tech companies is conceptualised amongst political economy scholars with a focus on different dimensions of this process. Shoshana Zuboff identifies surveillance capitalism as the result of extensive extraction of behavioural data from individuals as they interact with digital environments (social media, search engines and other online platforms) and the commodification of this personal data by large tech companies. These tech companies become powerful through their ability to gather vast amounts of data on individuals, extract knowledge about people from data and influence their behaviour, preferences and decisions for commercial gains (Zuboff 2019).

While Zuboff focuses on behavioural data that is produced by unpaid labour performed by consumers with their digital activities, Philipp Staab focuses on the establishment of proprietary markets by the large tech companies. Producers and consumers are active on proprietary markets and large tech companies extract rents. These proprietary markets are the foundation of the large tech companies’ power and the immateriality of products is what enables that power.² The non-rival and potentially scalable character of immaterial products in the digital economy makes it possible to sell large quantities for

²Philip Staab is not alone in this diagnosis. Sabine Pfeiffer notes that the ‘special significance of the immaterial ultimately inspires almost all diagnoses regarding the internet and the digital. You could say that the statement that the immateriality of the digital changes everything is legion’ (2021, p. 45) (Translation from German by the authors).

low costs or even supply them for free, with the aim of establishing vast user populations and enabling network effects which attract more users. This dynamic facilitates power concentration and the establishment of winner-takes-all markets. Staab identifies four strategies with which large tech-companies exercise control over the proprietary markets they establish, and data is the enabler of this control. Information control through the exclusive appropriation of market data (transactions, stocks and prices) generated on proprietary markets is the most important control strategy that enables the other three: control over access, prices and performance on the proprietary markets (Staab 2024).

For Nick Srnicek, contemporary capitalism revolves around the extraction and use of data. He identifies platforms as a new type of company that enables interactions between two or more users and has ‘data extraction built into its DNA’ (Srnicek 2017, p. 89). Through their superior access to data, platforms become lead firms in various industries; not only those that directly target consumers (B2C/C2C) but also those that mediate between organisations (B2B) (Srnicek 2017). Ben Tarnoff (2022) argues in a similar direction, terming the new organisational form as *online malls*. Online malls can be digital social media applications such as X and Facebook, online shopping applications such as Amazon or a ride hailing service such as Uber. He also connects to Staab’s analysis of proprietary markets by defining online malls as ‘privately owned public spaces’ (Tarnoff 2022, p. 86) that facilitate commercial activities (buying) as well as social activities (hanging out with friends). What distinguishes the online mall from the bricks-and-mortar mall is that ‘everything one does makes data’ (Tarnoff 2022, p. 86). The digital traces left by users of online malls are used to develop and refine the algorithms of these online malls and they are the main source of rent collection.

In her theory on intellectual monopoly capitalism, Cecilia Rikap identifies *data-driven* intellectual monopolies as a sub-type practiced mainly by the large American and Chinese tech companies. The economic power of these intellectual monopolies lies in their ability to capture data from individuals and organisations and transform them into digital intelligence by processing them ‘in ways that trigger multiple successive innovations’ (Rikap 2020, p. 440). Intangible assets developed from data give tech companies an innovative edge which they continuously expand, accumulating more intangible assets in the process. In such a way, established data-driven intellectual monopolies not only rely on internal capacities but also organise innovation networks around them that contribute to their innovation process but do not benefit from the gains (Rikap 2020, 2023).

Whether it is the extraction and commodification of personal data (Zuboff 2019) or data as the central control strategy exercised by the large tech companies on their proprietary markets (Staab 2024), or whether it is the establishment of new business models in the form of platforms (Srnicek 2017) or online malls (Tarnoff 2022) or data as the most important tool to establish data-driven intellectual monopolies (Rikap 2020, 2023); for all the authors, data extraction, its commodification and use features as the central tool enabling the lead firms of the digital economy to gain and maintain their power positions. And for their diagnosis, the assumption of the immateriality of products (digital products) is central. This is a convincing finding for sectors or niches in which products are predominantly immaterial and tech companies can be clearly identified as lead firms that generate revenue from digital products.

This strand of research has greatly advanced our understanding of how the business models of large tech companies extract value from data, and about the social effects of their emergence and their ubiquity. However, such hierarchical or captive forms of governance through tech companies are not necessarily the norm for conventional sectors in manufacturing that produce and sell predominantly material products (Ponte and Sturgeon 2014). Sabine Pfeiffer therefore questions whether such analysis of the current stage of capitalism (defined as digital) really takes into account all economic sectors or only a specific segment which mainly trades in immaterial products (Pfeiffer 2021, p. 49). With our analysis of data use in GVC, we hope to contribute insights into which aspects of the appropriation and utilisation strategies of the large tech companies also apply in sectors in which the immaterial element is intertwined with physical products and processes.

In sectors producing material goods, we encounter a complex entanglement of established lead firms and suppliers, some of which work on the development of digital business models themselves, in addition to their physical products. Technology providers in this context provide some preconditions for the economic utilisation of data in bricks-and-mortar industries. However, since business models constitute hybrids between data-centred strategies and conventional operations, we hypothesise that they will not be able to establish themselves as new lead firms by data extractivism and monopolisation alone. Furthermore, the development of data-based applications requires domain-specific knowledge, which continues to be located with employees in companies of the respective industries. Therefore, we argue that it is important to look beyond big tech dominance at this stage of the digital transformation of the economy, in which data plays a growing role not only in the consumer-facing digital economy but also in inter-firm relationships.

To conceptualise the function of data for intangible assets along the value chain we propose integrating the concept of the data value chain (DVC) into GVC research as a concept that theoretically links data and intangibles. It explains how data contributes to intangible assets and to their uneven (global) distribution (UNCTAD 2019). DVCs are not separate from physical processes, but are an additional digital layer that gets integrated into GVC. In their paper on virtual value chains, Rayport and Sviokla were probably the first to write about ‘two interacting value-adding processes’ in the physical value chain (PVC) and the virtual value chain (VVC) (1995). Following, the DVC concept has been discussed in business, policy and computer science circles since the 2010s (Alaimo, Kallinikos, and Aaltonen 2020; Curry 2016; European Commission 2014; GSMA 2018; Miller and Mork 2013; UNCTAD 2019). The DVC concept maps out and conceptualises the distinct process steps that transform data into knowledge products. Different authors propose varying numbers of chain elements (Faroukhi et al. 2020) covering more or less fine-grained the process steps of data generation, processing, transmission/storage, analysis and use. This is not a purely technical process. Instead, each step requires workers with a specific skill set to perform the necessary tasks.

The discussion on the relationship between data and intangible assets in this section, forms the second building block of our conceptual framework. Data played a role for companies far before the development of the internet but has gained a new level of significance through the easy availability and wide utilisation of digital data. The collection, processing and analysis of digital data in data value chains makes a growing contribution to companies’ intangible assets. At the same time, the acquisition and monetarisation of

data is characterised by a new thrust towards power concentration epitomised in large American and Chinese tech companies. In what follows, we analyze the forms of data utilisation for the production of intangibles in traditional industries and discuss whether their forms of data acquisition and valorisation result in similar forms of power concentration as in the digital economy.

3. Methodology

The theoretical cornerstones on data in GVC outlined above address the question of how data contributes to intangible assets, and therefore becomes a valuable asset itself. In the next step, we conduct an analysis of how different types of data are used to develop specific intangible assets and the changes in power relations that arise in the process. First, we lay out a data typology that conceptualises data from its place of extraction (transactions, products and processes) and the unique information it holds. Second, we present case studies on how the three types of data we identify contribute to intangibles in manufacturing value chains with different effects on upgrading and governance.

The data typology is a condensation of our findings from 88 semi-structured interviews conducted between January 2020 and May 2024, predominantly online.³ Interview partners were mostly middle and senior managers recruited from manufacturers and (industrial) software companies located in Germany that build digital services and develop digital business models (50), manufacturers that use digital services (13) and experts on the industrial internet and digitalisation of manufacturing industries from industry and academia (20). The three case studies on the use of transaction, product and process data in manufacturing value chains presented in section Five draw on a selection of this empirical material (a detailed list of interviews is provided in the Appendix). Companies and organisations for interviews were selected through desk research on three manufacturing sectors in Germany that actively develop digital business models: automotive, mechanical engineering and component manufacturing, identification of most relevant players and accounting for a variety of approaches to the development of digital business models. The interviews were transcribed or documented as protocols and analysed according to the method of qualitative content analysis (Mayring 2014) using a mainly inductive, that is a theory-generating process of category formation for the development of the typology and a deductive, that is, theory-led approach of coding the material for the case studies. The coding of the material was predominantly performed by one person, using the qualitative data analysis software MAXQDA and accompanied by discussions among the authors for inconclusive segments of the interviews.

To develop the data typology the main focus for the analysis of the material were the ‘origin’ and the ‘content’ of the data. It resulted in the inductive construction of the data types ‘transaction’, ‘product’ and ‘process’ data. After the construction of the three data types we validated the typology’s generalisability by applying it to the digital business

³Participants were interviewed solely in their capacity as experts on digital business models, industrial sectors and value chains. No personal information of interview partners was incorporated into the data analysis. Prior to each interview, interview participants were informed about the content and goals of the research project, and were told that the information they provide would be used for academic publications in anonymised form. Interviews took place only after interview partners gave their consent.

models of more than 50 companies that have data as an important part of their business model in a variety of fields: digital technology development, digital infrastructure provision, manufacturing and retail of consumer and commercial goods. The process of applying the data typology to companies' digital business models involved an analysis of the companies' websites identifying the service a company offers (e.g., predictive maintenance, a business process application or a fintech solution that enables financial transactions) and the data type that is used. Most companies business models could be allocated to one of the three data types, but the exercise also led to a refinement of the typology. We added two subcategories for each type and found a fourth data type, transmission and storage data, which we did not integrate in the analysis.⁴

The case studies are based on a sub-sample of the above-described interview material. The transaction data case study is based on 15 interviews with B2B transaction platform providers and manufacturing companies that cooperate with the platforms. The product data case study is based on six interviews with employees from one construction equipment manufacturer, particularly its digital service development department and the Internet of Things (IoT) platform they cooperate with. The process data case study is based on ten interviews with one machine and process health solution provider and one manufacturer that uses their solution. The categories for the deductive qualitative content analysis of this data subsample were developed in section Two of this paper: (1) the intangibles the data is contributing to, (2) possible upgrading opportunities for the involved actors, (3) the governance of the value chain and possible changes. The following sections introduce the main findings of our data analysis, presenting the data typology and the main findings from the three case studies.

4. Data in Manufacturing Value Chains — A Typology

Data is generated and insights from data are used at various stages along value chains, from R&D to product after-sales services. In this chapter, we provide a data typology that highlights the dispersed generation of data along a value chain, identifies the nodes of data generation (e.g., interaction on B2B market places, use of a consumer products or the production process in a factory) and locates where value can be generated.

We consider a data typology necessary since, to the best of our knowledge, research on the political economy of data lacks a suitable instrument to study in detail how data affects companies and value chains. Existing data categories do not entail a value chain perspective on data and remain rather descriptive. The 2019 digital economy report by UNCTAD compiled several existing data categories, such as personal or non-personal data, private or public data, data for commercial or governmental purposes, data used by companies (corporate, human resources, technical and merchant data), non-structured vs. structured data, instant or historic data, volunteered, observed and inferred data, sensitive and non-sensitive data, B2B, B2C, government to consumer (G2C) or consumer to consumer (C2C) data (UNCTAD 2019, p. 29). Further

⁴Transmission and storage (TS-) data is located on the infrastructure level of the technology stack. It is data in its basic technical form, removed from its information layer that gives it unique value. At this layer of the technology stack transaction, product or process data take the same shape, bits (binary digits) — zeros and ones — when stored or transmitted through a data cable or waves when transmitted through wireless networks. TS-data is not included in the analysis as data in this form is less important for the production of intangibles.

differentiations were made between consumer and machine data (Andreoni and Roberts 2022, p. 11), between transaction-data and IoT data (Alaimo, Kallinikos, and Aaltonen 2020) and product data was highlighted as a particular type (Porter and Heppelmann 2014). We take up some of the above-described characteristics and distinctions in our data typology: e.g., B2B and B2C data, machine, consumer, transaction and product data. However, we move beyond merely descriptive terms, highlighting the origin of data from a value chain perspective and connecting it with distinct application scenarios. This provides a suitable access point to analyse the production process of intangibles. We conceptualise the data types generated at these nodes as transaction, product and process data, respectively. The following data typology systematises these data types according to their information value and function within value chains and business models (for an overview see Table 1).

Transaction data is observed in two forms. (1) *Social transaction data* is data on consumer behaviour and preferences generated through interactions between users in online communities; often social media platforms. Applying social media analytics (such as natural language processing, share of voice, behaviour and sentiment analysis) generates insights into what kind of posts on TikTok and Instagram are liked by users, what they post themselves and who they follow. Such insights have an impact on product development and operational processes. (2) *Economic transaction data* is generated through market transactions, such as data on sales, prices, lead times, delivery and production locations on B2C or B2B e-commerce platforms or data on pick-up location, destination, driver location and ride requests on a ride-hailing platform. This data enables better matchmaking between the multiple sides of a market, generates insights into business

Table 1. Data typology.

Types of data		Data source	Data points (examples)	Business models
Transaction data	Economic	Market transactions between two or more participants	Sales, demand, prices, lead times, delivery and production locations	e-Commerce, fintech products, ride-hailing
	Social	Interactions between users or between content and users	Likes on social media, content of a user's post, follower networks	Social media apps, social networks
Product data	Consumer	Product usage	Use duration, used functionalities, location of the product, environment of the product	Development of internet-connected consumer products and provision of individualised content and functions
	Commercial	Product usage	Location of the product, machine parameter, machine utilisation, environment of the product	Smart after-sales services, predictive maintenance, machine data analytics
Process data	Digital	Firm-internal digital business and administrative processes	Sales numbers, procurement orders, HR information	SaaS for business data processing
	Physical	Interconnected equipment (manufacturing, logistics, transportation)	Machine parameters, state of the product in production, production frequency, GPS	IIoT platforms, SaaS for process data analysis

Source: Authors.

processes and creates transparency into supply and demand for the company that collects this data.

Product data is data gathered from physical products that are connected to the internet through sensors and IoT technology or from digital products (Porter and Heppelmann 2014). Products can be (a) consumer products such as electric toothbrushes, vacuum cleaner robots and cars, as well as less-tangible products such as online games or (b) commercially used equipment such as elevators, production machinery and railway locomotives. The data gathered from these internet-enabled devices and digital products generates insights into how and in what environment these products are used by private and commercial customers. *Consumer product data* and *commercial product data* is primarily of interest to producers of the product, as it helps them to innovate and improve their products. What they offer customers in exchange are better after-sales services, e.g., remote operation of a vacuum cleaning robot via a smartphone app, predictive maintenance for a car, elevator or manufacturing equipment that reduces downtime. From data on the technical condition of the product, produced through IoT technology, insights on user behaviour can be inferred, e.g., a smart boiler registers the showering behaviour of the user and can draw conclusions from it, such as that interruptions of the regular use can be interpreted as absence from home. Data from commercially used smart products also contains sensitive information on a company's operations, e.g., by registering the degree of machine utilisation and details on the machine operation or the travel routes and the environment of mobile equipment such as locomotives or automated guided vehicles.

Process data is data that is gathered from processes that run in the physical world (e.g., manufacturing or logistics processes) or from digital processes, such as business processes managed through an ERP system (financial accounting, supply chain management, procurement, human resource management etc.). This data category is mostly relevant in the B2B field. The core technology that enables the collection of *physical process data* is the IoT. Through the installation of sensors, data on physical processes can be collected from various devices that are involved in a certain process, e.g., the manufacturing equipment involved in the production of goods or the equipment involved in the logistics process of shipping a product to its destination. The collection of physical process data throughout the manufacturing process is at the core of what smart manufacturing or Industry 4.0 envisions. It promises to lower production costs by optimising the production process and enable greater customisation in mass manufacturing (Kagermann, Wahlster, and Helbig 2013). *Business process data* is gathered and integrated from a sequence of a company's internal digitally tracked activities. It could be a software suite that integrates a hotel's operational data: bookings, check-ins, payments, breakfast reservations, laundry orders, bed sheet supply etc. It could also be an e-commerce store's software suite that manages incoming orders, stocks and in-process orders with manufacturers, scheduled advertising campaigns or an HR software that supports the management of employees (shift and holiday allocation, training programs, sick leave etc.).

We believe that this differentiation of data types along their sources (transaction, products, processes) is a useful analytical tool to understand how data in its diversity contributes to companies' intangible assets, is used in digital business models and for companies' internal digitalisation processes. While the typology makes a clear distinction

between these three sources of data, single data points can be relevant at more than one node in a value chain, e.g., the datum ‘price’ can be recorded and processed as part of economic transactions as well as in digital processes (e.g., a company’s supplier management system) and sensor data on the state of a product (e.g., in use/idle) can be analysed in the context of a physical process or product use. A datum develops its unique meaning through the specific interaction in which it is generated at each of the three nodes in value chains: interactions between people via digital interfaces (transactions), interactions between people and objects (product use) and interactions between objects and between people and objects (process data). The typology is grounded in existing digital business models and while repurposing and translating of data points is theoretically possible, it is rarely empirically observable.

5. Use of Data in Intangible Assets — Three Case Studies

We look at three digital business models that use the data types introduced above, analysing (a) at which nodes in the GVC and by whom data is generated, (b) the intangible assets data is contributing to, and (c) how this changes the governance of the chain and affects the up- or downgrading for certain actors. The three case studies focus on digital manufacturing platforms, digital services for construction machinery and a manufacturing process analytics software. The cases were selected for illustrative purposes as they represent common types of intangibles and business models that companies are developing based on digital data. The case studies show how digital business models have different effects on value chains and illustrate the complexity of power constellations along the data value chain for an overview of findings see [Table 2](#).

5.1. Transaction Data: Market Intelligence for Better Matchmaking

One business model that builds on economic transaction data in the industrial field is pursued by digital manufacturing platforms. Those platforms offer improved matchmaking between industrial buyers and suppliers based on the analysis of data collected from manufacturers, customers and their interactions. Mechanical components is one industry where such platforms emerge. Start-ups from Europe and the US combine IT capabilities with a good knowledge of the industry, curate a network of manufacturing partners around them and forward the orders they receive from industrial customers to partners in their network (Butollo and Schneidmesser [2021](#), [2022](#)). The processes offered by manufacturers include laser cutting, computerised numerical control (CNC) processing and 3D printing of different kinds of metals and synthetic materials. The customers of these platforms come from all kinds of manufacturing industries, including mechanical engineering, robotics and medical devices. To become part of a platform’s partner network, manufacturers have to provide detailed information on their capabilities, machines, size and location. Customers have to upload the technical drawing and 3D model of the designed component, including measurements, tolerances, required materials and processing technique. Based on this data, digital manufacturing platforms try to find the best possible match between a customer’s needs and a manufacturer’s abilities, collecting further data on production costs and prices.

Table 2. Data use in GVC.

	Digital manufacturing platform	Digital services for construction machinery	Machine health solution
Data type	Economic transaction data	Commercial product data	Physical process data
Data points	<ul style="list-style-type: none"> Manufacturers capabilities Prices Delivery times Component design properties 	<ul style="list-style-type: none"> Location Machine parameters such as temperature and sound Volume of pumped concrete 	<ul style="list-style-type: none"> Vibration of rotating machine components Temperature at different locations of production machines
Intangibles	<ul style="list-style-type: none"> Market intelligence Knowledge of organisational processes of the mechanical component industry 	<ul style="list-style-type: none"> Knowledge of machine use that informs product development Data and data analysis capabilities to offer digital services 	<ul style="list-style-type: none"> Efficient anomaly detection by combining machine data with vibration analysts' expertise Training of a machine learning algorithm through access to big data
Governance	<ul style="list-style-type: none"> Platform as new actor shaping chain governance but no domination (yet) Potential for greater power concentration in case of a market consolidation 	<ul style="list-style-type: none"> The concrete pump manufacturer strengthens its position vis-a-vis customers but no domination IIoT platform and AWS as new actors that provide technical infrastructure 	<ul style="list-style-type: none"> No domination yet but potential of knowledge concentration (data + vibration analysis' expertise) in the hands of the software solution provider Cooperative behaviour of maintenance personnel essential to learn from customer data
Upgrading	<p>Component manufacturer:</p> <ul style="list-style-type: none"> Channel upgrading through easy access to new customers and markets Potentially functional downgrading through loss of complementary services <p>Customers</p> <ul style="list-style-type: none"> Process upgrading through time reduction in procurement processes 	<p>Equipment manufacturer</p> <ul style="list-style-type: none"> Functional upgrading by expanding from a hardware producer to a digital service provider Potential for product upgrading by integrating usage data into product innovation <p>Customer</p> <ul style="list-style-type: none"> Process upgrading through reduced downtime and increased process efficiency 	<p>Manufacturer</p> <ul style="list-style-type: none"> Process upgrading when ML-software replaces manual monitoring

Source: Authors.

Intangibles: The data contributes to the intangible assets held by the platform provider; it could even be claimed that the data enables this business model. Digital manufacturing platforms achieve an unprecedented centralisation of knowledge on manufacturing processes, designs and prices and transparency about manufacturing conditions on a global scale. This knowledge is the basis for their matchmaking service; customers can save time and reduce the costs of procurement and manufacturers gain access to new customers via the platform. One platform representative claimed that his platform reduces the time traditionally needed to fulfil an order by 50 per cent (ETD1a⁵).

⁵Interviews are labeled in the following manner: The interviews related to each case study are given a separate code (ETD = economic transaction data case study; CPD = commercial product data case study; PPD = physical process data case study), all other interviews are labeled as experts (EXP), the number stands for the interviewee, a letter is added in case we conducted more than one interview with one person.

Digital manufacturing platforms not only provide matchmaking services based on data collected from transactions between manufacturers and customers; the four platforms also utilise the data to improve and expand their services, for example by developing an accurate instant pricing tool. This is an important step towards a sustainable business model for these platforms, as manual quotation is a knowledge-intensive and therefore expensive aspect of the business relationship. To calculate a realistic price, the requested materials, required processing techniques, lead time, batch size and the properties of a technical drawing are compared with automatically generated benchmarks from the platforms' vast database, employing machine learning or more traditional statistical computing methods. One platform representative claimed that their machine learning algorithm had already analysed more than one million computer-aided design (CAD) files to automatically calculate prices (ETD3a). Another platform adds a kind of digital twin to its portfolio, simulating a component's manufacturing process to take all the relevant parameters into account to avoid a miscalculation of the overall production cost that would create losses for the platform (ETD2d). Platforms also expand into pre-production services. They develop software to test the manufacturability of a component design by utilising the vast amount of data on machine-part designs and CAD drawings that are uploaded to the platforms by their customers. Another area of expansion is to automatically generate feedback on a component design, suggesting simpler and cost-saving processes or materials.

Impact on Governance and Upgrading: Most of the well-known tech companies catering to consumers (GAFAM and BATH) that have gained quasi-monopolistic market positions have transaction data as an important part of their business model, whether data on social transactions (Facebook and X) or economic transactions (Alibaba's Taobao and Amazon Market Place). One advantage of these business models is that accessing and processing transaction data from individuals and organisations is relatively easy since the companies' value proposition is very straightforward: they reduce transaction costs for their customers and in exchange, they require access to certain data points which consumers and companies are willing to share.

The same logic (easy access to data + network effects + information concentration) underlies the digital manufacturing platforms in the mechanical component industry. However, no single platform has been able to claim a market position which would result in a relationship of dependence on the side of manufacturing partners and customers. We have identified 64 platforms globally in this industry as of 2022. In such a fragmented market, platform companies need to invest in a good relationship with customers and manufacturing partners to utilise cross-side network effects. A good balance of both user groups is important to keep them engaged on the platform; this seems to be more relevant than a very large network of manufacturers. Though platforms can centralise an unprecedented amount of data with their business model, they have only limited regulative tools to exercise pressure on manufacturers. This is reflected in manufacturers' platform strategies; a majority currently use platforms mainly to utilise excess capacities that they cannot fill with orders from traditional customers and many manufacturers cooperate with more than one platform. For manufacturers, the platforms offer a form of channel upgrading; they gain orders from customers that would otherwise be out of their reach or even gain access to new markets. This is particularly the case for companies in Eastern Europe and China.

The platforms generate their profits through transaction cost savings for manufacturers and industrial buyers. They also try to expand their profit margin by exploring the above-mentioned pre-production services that can be offered based on the data they collect. The ability to generate extra profits beyond the transaction cost savings they enable is currently limited. However, should the market configuration change in the future or should one platform become the dominant player in the industry, the bargaining relationship could tilt in favour of that platform and result in enhanced competitive pressures for the manufacturing partners as the conditions become non-negotiable. For manufacturers in high-wage countries such as western Europe, this may particularly be the case when platforms involve companies on a global scale, putting them into direct competition with manufacturers from low-wage countries that previously did not have good access to markets in the EU and the US. Manufacturers are then effectively benchmarked against the market participants that are globally the most efficient, fastest and cheapest. A similar dynamic has been observed in the development of Amazon Market Place over the past 20 years (Weigel 2023).

5.2. Product Data: Insights into Machine Condition and Use

Data plays a growing role in the mechanical engineering industry. Equipment manufacturers explore new possibilities to develop digital services and business models as an add-on to the machinery they produce. In the high-end market, this is considered to be an important strategy to continuously justify the price premium paid by customers while mid-range alternatives of good quality are available at increasingly competitive prices (EXP1; CPD1a). A German mid-sized company that is a market leader in its product segment — concrete pumps — is exploring these opportunities by developing digital services for its products. The foundation of these services is *commercial product data* that is collected from the concrete pumps in the field. Sensors that are installed within the pumps collect information on their condition, utilisation and location. By employing IoT technology, the data is sent to an Industrial Internet of Things (IIoT)-platform where it is processed and analysed.

Intangibles: The manufacturer offers services addressing its customers' different pain points: remote diagnostics, data-driven maintenance, machine parameter analytics, digital billing and theft protection. For remote diagnosis and data-driven maintenance, the owner is notified of critical machine conditions based on data collected from their machines. This helps to identify the issue and take appropriate measures. The owner is also notified of maintenance intervals and when replacements of parts are necessary. This is meant to make the provision of spare parts easier and reduce downtime. Furthermore, key machine parameters, such as delivery rate, machine utilisation and fuel consumption can be analysed to enable the user to take measures to reduce unproductivity, wear and fuel consumption across the fleet. The digitised billing process generates daily updates on the volume of pumped concrete, saving the pump operator the manual calculation of this billing parameter in the end of each month. As theft of equipment from construction sites is an issue, an Anti-Theft-Function is offered that notifies the equipment owner when the pump leaves a defined area.

Gaining access to machine data in the field by providing these services creates a new level of transparency into the utilisation of its products. Intangible assets can be

generated in two ways from this; combined with novel capabilities in software development and data science, this new depth of knowledge on how their products are utilised by customers informs the further product development process, potentially leading to better functionalities. The manufacturer is also developing a new digital business model, utilising its domain-specific knowledge in ways that expand beyond the physical product.

Impact on Governance and Upgrading: Integrating digital services into the concrete processing value chain changes the constellation of actors and their position. To offer its digital services, the concrete pump manufacturer is cooperating with an IIoT-platform that contributes the infrastructure and technical implementation of the services. The IIoT-platform hosts data and services on servers from Amazon Web Service (AWS). According to the concrete pump manufacturer, he contributes the design of the services and the domain know-how for data analysis (CPD1b, CPD1c). By adding digital services to their portfolio, the concrete pump manufacturer intensifies its relationship with its customers: along with the hardware sale and maintenance contracts, he additionally provides his customer with information and feedback on the operation of the equipment, based on the collected data. The customer pays for this service and the manufacturer gains knowledge about customers' operations and user behaviour. To expand its product portfolio to such services amounts to functional upgrading for the concrete pump manufacturer. In addition to its hardware business, the equipment producer has become a digital service provider, gaining experience in the application of data analysis and digital technologies in the construction machinery industry. The enhanced depth of knowledge on machine operation practices also enhances the company's innovative capabilities, creating opportunities for product upgrading. For instance, this knowledge can be used to eliminate weak points in the construction, resulting in reduced downtime. It can also be used for making decisions on which features to develop further and which to discontinue.

In this way, data-based business models emerge as an important variable of competitiveness. Companies that are able to acquire and centralise user data can not only tap additional sources of revenue, but also base their innovativeness on product use data. While the access to data therefore shapes competition between producers, there is no evidence for a shift in power relations within the concrete value chain. Data is not simply available to pump manufacturers, they need to convince their customers to share commercial product data. This is a challenge because manufacturing companies consider their utilisation of machinery to be sensitive or even secret information. This scepticism among manufacturing companies in Germany about sharing machine data is reflected in a survey by the German Economic Institute and the Foundation of German Industries (Röhl, Bolwin, and Hüttl 2021) and was also emphasised by our interview partners. The concerns over the sharing of machine data are a constraint to the establishment of business models that use commercial product and physical process data (EXP1; EXP2; EXP3). Whether access to machine data is granted depends greatly on the clarity of the value proposition of the proposed service. The concrete pump industry has a relatively good precondition to demonstrate the value of the digital service and convince customers to share their data because damage to concrete pumps can easily inflict high costs on the equipment operator and data-based condition monitoring can decrease the risk of such an incident significantly. The services show potential for process upgrading on the side of the equipment operators, as

risks of damages and repair costs can be significantly reduced and pump utilisation can be improved (CPD1a).

Overall, the value created through the digital services for concrete pumps is distributed between the concrete pump manufacturer, an IIoT-platform as a technical service provider, the cloud infrastructure provider (AWS) and the pump operators. The concrete pump manufacturer tries to position itself as the major player in this field, becoming an important service provider. However, it is unable to take on a dominating role by exercising control over other actors in the chain, and this is unlikely to change in the future due to the high level of data privacy consciousness among manufacturing companies and limited possibilities to exploit network effects. The IIoT-platform provider and AWS play a subordinate role (CPD1b, CPD2) but commercially benefit from the provision of their services.

5.3. Process Data: Human-AI Collaboration for Production Line Reliability

The manufacturing process has been identified as a vast source of data in recent years that can be used for optimisation and cost saving. At the same time, manufacturing is a very difficult field to collect and make sense of data because of data privacy issues (as discussed above) and the heterogeneity of machine types and generations which record data in inconsistent data formats (EXP4).

Because of such difficulties, there appears to be a trend towards industrial technology companies offering rather narrow solutions with a clear use case instead of trying to utilise comprehensive data from one or several manufacturing facilities. Machine and process health are use cases which an industrial analysis solutions provider is trying to solve in various industries, among them for a German tissue paper manufacturer. Collecting *physical process data*, specifically vibration and temperature data through sensors from the manufacturers production equipment, the company offers alerts about anomalies in the machine operation and offers suggestions on how to remedy them and how to optimise throughput and yield.

Intangibles: The industrial analysis solutions provider offers its customers a full package service, from the installation of sensors on the machines, to data collection, analysis and evaluation; the solution provider stays involved in the day-to-day machine monitoring for the long-term. For the machine health solution, process data on vibration and temperature is collected in real-time and compared to historical data, using machine learning. Data access seems to not be a big bottleneck in developing this business model (PPD2).

Before alerts about anomalies in machine behaviour generated by the software solution are forwarded to a customer's maintenance staff on-site, they are validated by vibration analysts employed by the industrial analysis solution provider. For incidences that are forwarded to the customers' maintenance team, employees need to give feedback about what measures they have taken to react to the anomaly in temperature or vibration and what the cause was. This feedback is essential to further improving the solutions' accuracy.

These details on the machine health software application are crucial to understanding how data becomes an important part of the intangible assets and business model of the industrial analysis solutions provider. The customers' process data is what enables the

company's business model, but its actual value is realised only in combination with the expert knowledge of vibration analysts. According to an employee of the solution provider, the importance of expert validation will not decrease, even though accuracy of incident identification will increase over time. The information derived from the customers' machines in combination with the software solution alone would not reach the accuracy needed in the industry, as unplanned machine shutdowns can impose high costs for the customer (PPD3). Additionally, the machine learning algorithm that helps identifying anomalies in machine behaviour is periodically improved based on anonymised machine and incident data collected from customers. Customer data is therefore helping to make the software solution more and more accurate and competitive, developing significant network effects.

Impact on Governance and Upgrading: The industrial analysis solutions provider enters a variety of value chains as a new actor, in our case study the tissue industry. The potential for upgrading through using the machine health solution is most explicit when it is replacing a manual maintenance process (staff walking from machine to machine and measuring vibrations and temperature with a portable measuring device). Such locations experience process upgrading as an increase in maintenance efficiency and therefore perceive the solution provider as clearly creating value (PPD4). The experience of upgrading is more subtle for manufacturing locations that already have some kind of machine monitoring system in place (PPD1a).

At the current stage, involving the machine health solution provider does not have a strong effect on the governance structure of the industries it enters. It becomes one among the many software providers large industrial companies engage with. They still struggle to put exact numbers on the maintenance cost savings they realise to demonstrate that they actually help customers save more in maintenance costs than the fees they take for the service which are calculated per sensor installed (PPD2). The superiority of a process and machine health solution that combines extensive data collection from customers processes with ML-based data analysis and vibration analysis expertise, can lead to a concentration of core manufacturing knowledge in the hands of the industrial analysis solutions provider in the long-term. With the ML-based machine health solution, the productivity of vibration analysts is increased significantly. One of our interviewees explained that the vibration analysts of the solution provider, together with the ML-based software, can monitor a much larger number of machines than maintenance staff that monitor machine health manually; the software already preselects which machines might actually show an issue and the vibration analyst subsequently only looks at these machines (PPD3). The obvious cost advantage of highly productive vibration analysts at an external technology company might convince more and more actors to outsource machine monitoring tasks, making the industrial analysis solutions provider we studied an indispensable actor in manufacturing value chains.

5.4. Discussion

The case studies show some general trends and differences with regard to the three types of data. The data types contribute to developing different kinds of intangibles. From economic transaction data, the digital manufacturing platforms gain a superior market overview that enables a better matchmaking between manufacturers and industrial buyers.

From product data, the machinery manufacturer can develop digital services that create greater machine reliability and at the same time inform their product development. Based on process data, the industrial analysis solution provider can develop a solution that can enhance productivity by predicting process disturbances and can employ vast data sets which it collects globally to retrain its machine learning model, thereby constantly improving its product.

The importance of expert and domain knowledge varies across the data types. The intangibles developed from transaction data require less integration with domain knowledge to enfold their value. On the contrary, expert knowledge plays an important role in developing intangibles from product and process data. In the case of product data, the digital service is offered by the equipment manufacturer, not an external technology provider. This is a pattern that can be observed for business models based on product data more generally. It is mostly the product producer who offers digital services; they have the best knowledge of the product and customers' needs and can make use of the collected data in product innovation. For the case study on physical process data it is not the knowledge of a specific domain that is relevant, as the solution can be used across different industries such as tissue paper, gas, oil and food processing. However, intimate knowledge on and experience with machine vibration is needed; this is not only relevant for software development, but vibration analysts' evaluation of the data is an integral part of the service.

In all cases, the technology providers develop intangible assets and digital business models with the data they collect from involved parties; they create additional functionalities and value from it. For their users, the application of such functions can result in industrial upgrading, for instance by providing additional sales channels (channel upgrading) or enhancing productivity (process upgrading). The realisation of upgrading is a necessity to convince customers of the value of the new solutions, incentivising them to contribute their data. It is the foundation of a functional division of labour, by which manufacturing companies benefit from the inputs of technology providers.

While the feasibility of the business models of technology providers rest on mutual benefit, there is the possibility that these interactions could develop towards a relationship of dependence in the long-term. In the transaction data case study, monopolisation processes could emerge through network effects (as in the consumer e-commerce segment) which would put the strongest platforms in a better position to increase their share in transaction revenues. The platforms could also take over some of the value-creating tasks previously performed by manufacturers, such as consulting on cost efficient product design, resulting in functional downgrading. In the process data case study, the reliance on the machine health solution and technology companies' vibration experts could result in dependence on the solution, as manufacturers no longer develop their own expertise in vibration analysis. In the case of product data, digital services could develop into a vital ingredient for product development, which sets those companies that acquire data from product use in a superior market position. In this way, data-based intangibles could drive concentration dynamics in specific industrial segments. However, as our case studies demonstrate, such concentration is currently more a theoretical possibility than empirically observable, as all these business models are still in an early stage and have to prove sustainable in the long-run.

6. Conclusion

In this article, we traced the origins of the economic potency of data to understand the precise impact of datafication on conventional economic sectors. We developed a data typology that differentiates transaction, product and process data and systematises what types of data contribute to the development of different kinds of intangibles: superior procurement coordination, transparency of machine conditions and reduction in manufacturing process disruption. We found that the realisation of upgrading effects for customers is an important precondition for the success of the business models of digital service providers, as industrial customers will only be prepared to share their data if they can see concrete benefits to their operations. Our interpretation of this finding is that there is no swift and immediate path towards a power shift from manufacturers towards digital service providers as the latter will need to demonstrate a mutual benefit to gain access to data. The applicability of this finding may be different across data types as their sensitivity varies. Economic transaction data is less competition-relevant (certain data always needs to be shared with suppliers) than product and process data, and among these two data on the whole process is more critical than on the operation of single pieces of equipment.

We also point to potential sources of power concentration, a development that is possible, but not inevitable. Independently of whether the datafication of manufacturing results in new industrially-oriented tech monopolies or not, our research underlines the importance of immaterial value creation as an extension of traditional manufacturing value chains. Data and those who provide the means of production of data-based intangibles will certainly play an important role in shaping the manufacturing industries of the future. The strength of the suggested approach — examining the production process of data-based intangibles — is its focus on the specific actor constellation in the processes of data generation, use and monetarisation. It highlights the division of labour that enfolds in the process as well as the market-driven negotiations of the share of value each actor can capture.

Further applications of this proposed research framework to case studies on data-driven business models are required to develop a comprehensive understanding of how data contributes to intangible assets and its relationship to economic potency in certain sectors. In future research, further factors should be taken into consideration and discussed for different data types, such as the size of the data set, the heterogeneity and quantity of included variables, the ability to combine and connect different data sources and the role of digital platforms. Another dimension for further research on the distribution of power in data-enhanced GVC are the differences in the sensitivities of sharing data which vary across industries and are subject to existing power relations. Comparative research on the role of digital service providers in different industries and within varying governance settings could strengthen the empirical basis of a theory of the role of data and power dynamics in data-enhanced GVC.

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ORCID

Lea Schneidemesser  <http://orcid.org/0000-0002-1052-8648>

Florian Butollo  <http://orcid.org/0000-0003-0749-240X>

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