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Requirements For Incentive Mechanisms In Industrial Data Ecosystems

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Abstract

In the increasingly interconnected business world, economic value is less and less created by one company alone but rather through the combination and enrichment of data by various actors in so-called data ecosystems. The research field around data ecosystems is, however, still in its infancy. In particular, the lack of knowledge about the actual benefits of inter-organisational data sharing is seen as one of the main obstacles why companies are currently not motivated to engage in data ecosystems. This is especially evident in traditional sectors, such as production or logistics, where data is still shared comparatively rarely. However, there is also consensus in these sectors that cross-company data-driven services, such as collaborative condition monitoring, can generate major value for all actors involved. One reason for this discrepancy is that it is often not clear which incentives exist for data providers and how they can generate added value from offering their data to other actors in an ecosystem. Fair and appropriate incentive and revenue sharing mechanisms are needed to ensure reliable cooperation and sustainable ecosystem development. To address this research gap and contribute to a deeper understanding, we conduct a literature review and identify requirements for incentive mechanisms in industrial data ecosystems. The results show, among other things, that technical requirements, such as enabling data usage control, as well as economic aspects, for instance, the fair monetary valuation of data, play an important role in incentive mechanisms in industrial data ecosystems. Understanding these requirements can help practitioners to better comprehend the incentive mechanisms of the ecosystems in which their organisations participate and can ultimately help to create new data-driven products and services.

Keywords

Requirements; incentives mechanisms; data sharing; industrial data ecosystems

1. Introduction

The steady spread of information and communication technologies leads to the fact that data is increasingly a driver of change and economic growth [1]. Whereas in the past data was primarily used to improve internal processes, today it more and more serves as a strategic resource that forms the basis for the development of data-driven innovations and business models [2]. At the same time, however, data generation and data processing are neither the core competence nor the core business of most companies. In addition, it is increasingly no longer just the company's own data that is of interest [3]. On the one hand, large amounts of data are needed for meaningful analysis purposes, which is further reinforced by the trend towards artificial intelligence. On the other hand, the required data is often not generated within the respective company itself. As a result, data-driven innovation and economic value creation are less likely to be created by individual organisations or in traditional value chains. Instead, data-driven value creation takes more and more place in cross-industry, socio-technical networks - so-called data ecosystems [4]. This development implies that

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participation in data ecosystems is becoming increasingly likely and relevant for companies. Some authors even claim that ecosystem engagement is an urgent necessity rather than a choice for companies [5]. However, many companies are still reluctant to share their data with others and are therefore unable to take advantage of the potential and benefits that arise from participating in data ecosystems [6]. In particular in traditional sectors, such as production and logistics, data is still comparatively rarely shared across companies [7]. One main reason for this is seen in the fact that it is often not clear what incentives exist and ultimately how data providers can benefit when they offer their data to other actors in an ecosystem [8]. For this reason, a functioning and sustainable ecosystem requires fair and appropriate incentive mechanisms which motivate actors to participate in a data ecosystem [9]. To address this research gap and contribute to a better understanding about the structure of incentive mechanisms in industrial data ecosystems, we aim to answer the following research question in this paper:

Research question: *What are requirements for incentive mechanisms in industrial data ecosystems?*

The remainder of the paper is structured as follows: First, we give an overview of the theoretical concepts of industrial data ecosystems and incentive mechanisms. Section 3 describes our structured literature review and analysis process. Afterwards, we outline the identified requirements for incentive mechanisms in industrial data ecosystems. Finally, we conclude the paper with a discussion of the results and provide an outlook on future research topics.

2. State of the art

2.1 Use case example: Collaborative condition monitoring

Condition monitoring is the process of regular or permanent monitoring of a machine condition by measuring and analysing physical parameters such as vibration or temperature. The goal is to analyse the data from the machine sensors to detect behavioural patterns that may indicate a developing fault in the machine. This data is classically shared bilaterally, e.g. exclusively between the machine manufacturer and the machine operator. The idea of collaborative condition monitoring (CCM) is that data is not only shared bilaterally but multilaterally between all actors in an ecosystem [10]. This increases the amount of data available which in turn improves the results of the data analysis. Figure 1 gives an overview of a CCM use case. The component supplier shares lifetime or reliability relevant data about the machine components produced by him. In return, he gains access to operating data for his components and other relevant associated machine data. This enables the optimization of his components or new services, such as proactive spare parts management. Based on historical data from many machines in a wide variety of environments, the machine manufacturer can use AI methods to recognize how, for example, the availability and tolerances of the machines change in production. With this knowledge, the manufacturer can proactively contact the machine operator with a maintenance offer and generate increased customer satisfaction. For this, however, the machine manufacturer needs the operating and environmental data of the machine operator. The machine operator provides this data and benefits from the predictive maintenance service of the machine manufacturer with increased machine availability. However, the potential of CCM can only be realized in practice if data is shared by as many actors as possible. This also includes actors who may not generate any directly apparent added value by sharing their data. For this reason, incentive mechanisms are needed that address all actors and motivate them to participate in collaborative data sharing [10].

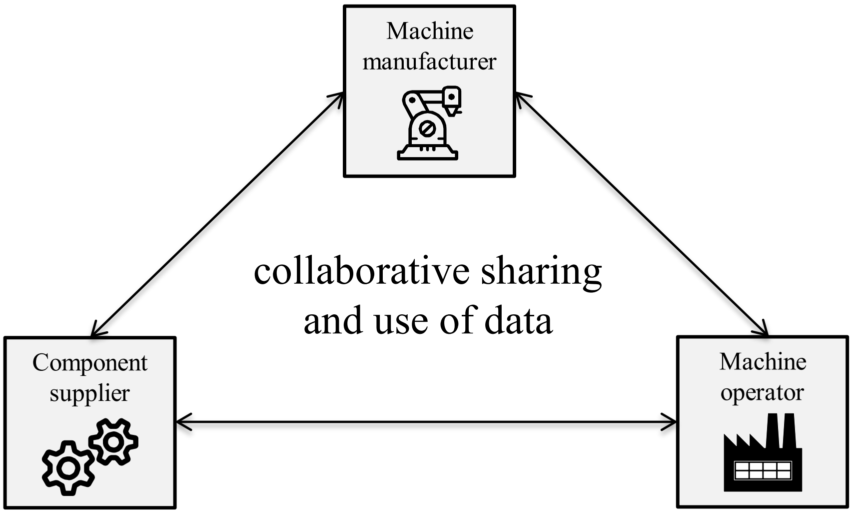

Figure 1: Collaborative condition monitoring use case overview [10]

2.2 Industrial data ecosystems

Data is often seen as the raw format that becomes information through processing. This information is then combined and interpreted to generate knowledge that can be used for decision-making processes or new business models [11]. This value creation process is also known as the data value chain [12]. A data value chain generally consists of the three phases: data collection, data interpretation, and data exploitation [8]. Data collection includes the generation and acquisition of data by e.g. sensors [13]. Subsequently, data analysis methods such as machine learning are used to process raw data into useful information. Lastly, in the exploitation phase, the information is integrated into business activities and translated into business value such as cost reduction [12]. Due to the development that data-driven services and products are increasingly based on the combination of multiple data sources from various actors, the different phases of the data value chain are often performed by different actors instead of one resulting in new forms of cross-company collaboration [14]. These forms of collaboration are also referred to as data ecosystems which, consequently, focus on the cross-actor generation, processing, and use of data with the aim of creating added value for all actors involved [15,7]. In this context, data ecosystems can generally emerge in the three domains scientific, government, and industry [16]. Since data ecosystems consisting of industrial companies in particular have not been well studied, we focus on industrial data ecosystems in this paper [17]. Data ecosystems are characterized by, among other things, complex interdependencies among their participants leading them in some cases to work cooperatively and competitively at the same time, which is also known as coopetition [18]. Based on the data at the focus of an ecosystem, different actors have varying relationships to it. This leads to different roles with a variety of functions that can be taken on [16]. At a minimum, there are the following three roles: Data providers who collect and provide data, analytics service providers who analyse the data, and data consumers who perform data exploitation activities [8].

2.3 Incentive mechanisms in industrial data ecosystems

Incentive mechanisms are studied in many different fields when it comes to encouraging people or organisations to do something in exchange for a reward. Incentive mechanisms in industrial data ecosystems are important for the following reasons: As described above, data-driven products and services are increasingly based on the combination of different data which originate from both internal and external data sources [19]. However, many companies are reluctant to share their data with others as the data may contain confidential and valuable information and sharing it could consequently strengthen competing companies [20]. Second, it is difficult to valuate what a data provider should get back for its data, e.g. in the form of money, as there are still no standardized methods for the monetary valuation of data both in research and practice [7,21]. Finally, all activities in the data value creation process incur costs, e.g. for maintaining the data and its quality along the data lifecycle [8,22]. Similarly, making data available for sharing creates costs in terms of effort and time for the data providers [23]. However, revenues are only generated in the data exploitation phase [8]. For these reasons, the expenses for all other activities that can be performed by different actors must be compensated by the revenues from the data exploitation activity in such a way that a win-win situation is achieved for all actors involved [24,8]. This compensation can be done in different ways such as a direct payment or indirectly through, for example, a service [8]. Incentive mechanisms should ultimately ensure that each actor is appropriately rewarded for sharing their data, to promote fair and sustainable collaboration in the ecosystem [25].

3. Research method

The objective of this study is to identify requirements for incentive mechanisms for data sharing in industrial data ecosystems based on findings from the relevant literature. We, therefore, performed a structured literature review following the approach by [26] and the guidelines by [27]. We chose Scopus as our scientific literature database because it contains more than 25,100 titles from more than 5,000 international publishers and thus promises great results for our field of interest, indexing the most relevant journals and conference proceedings [28]. We performed an initial search using the keywords "data ecosystem" AND "data sharing" AND "incentive". This, however, resulted in no hits. To overcome this shortcoming, we decided to expand and simplify the keywords. Therefore, we used "data sharing" OR "data exchange" AND "incentive" as our search query. We added the term "data exchange" because it is used synonymously with the term "data sharing" by some authors in the literature [29]. The results were limited to English language literature and peer-reviewed only. As a first set, this resulted in a number of 344 papers. Within this initial set of papers, we examined the titles, abstracts, and keywords in terms of relevance to our research question. We eliminated papers, for example, dealing with incentive mechanisms for sharing research data as conditions and incentives within these research data ecosystems are different from those in industrial data ecosystems [16]. This filtering process resulted in 17 relevant papers. We then performed a forward and backward search as suggested by [30] which resulted in 10 additional relevant articles. In addition, we added the 15 articles on industrial data ecosystems from a recent systematic review of the data ecosystem literature in which the authors selected and reviewed articles based on additional search terms in other prominent bibliographic databases [16]. This resulted in a total of 42 articles as the basis for the literature analysis process (see Figure 2).

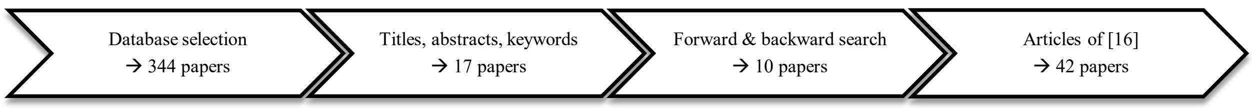

Figure 2: The structured literature review process

For the literature analysis, we followed an explorative approach to identify relevant similarities and interesting facts to answer our research questions [30]. The rationale for choosing this exploratory approach is the lack of theories on incentive mechanisms in industrial data ecosystems. To code the literature, we followed the grounded theory coding process [31]. Accordingly, open coding was first used to label the literature with categories that summarize the relevant content. Subsequently, relationships between the categories were identified by axial coding. Last, selective coding was applied to aggregate the identified categories into more general dimensions. In summary, we obtained five aggregated dimensions that represent, respectively, requirements for incentive mechanisms in industrial data ecosystems. These five requirements are described individually in detail below.

4. Results

4.1 Requirement 1: Ensure quid pro quo

One of the main requirements of incentive mechanisms mentioned in the literature is to ensure that each actor has to benefit through its participation in the data ecosystem [20]. Otherwise, it would not be rational for a company to participate in the ecosystem if the participation would lead to a worse company state [8]. Here, quid pro quo means that every actor who puts something into the data ecosystem, in the form of data, money, or any other effort, must also get something back. Particularly for data providers, it must be unambiguously and transparently clear how they can profit by sharing their data [24]. This requires that data providers must be adequately compensated for their data, for the costs incurred in collecting and storing the data, and for the risk they take in sharing it [8]. In general, therefore, it is necessary to consider within the ecosystem how the revenues, which are usually generated only when data are exploited, are distributed fairly [25]. For this it is required that the shared data is valuated in monetary terms, which is still a great challenge due to the special characteristics of data [7]. That is why some authors propose models that take into account proportionally how much contribution the shared data has on the revenue or lead to an improvement of the data-based service [13,8]. However, these models also have the challenge of calculating this proportionate added value of the total value. This is especially difficult when multiple data sets from different data providers are combined and analysed by one data consumer [8,25]. Nevertheless, a distribution of profits or the compensation of efforts does not necessarily have to be monetary for all actors. Instead, an actor may receive other forms of payment in return for their data, such as data or a service [24]. For these reasons, it is important to identify and quantify what added value each actor can receive through their participation in the data ecosystem. In this regard, there are often cases in which one's own added value is not directly recognizable for some actors [24]. If this is the case, the other ecosystem actors should transparently present and demonstrate this possible added value, e.g. by showing possible improved economic key performance indicators [13]. In literature and practice, there are increasing ideas to solve these challenges of profit distribution with blockchain-based tokens as these can be exchanged digitally more easily and securely than money, for example [32].

4.2 Requirement 2: Improve data quality

A second requirement identified in the literature is the incentive to share data with a high quality in the ecosystem. Since data is the basis for data ecosystems and the added value they create, it is important that the data in the ecosystem has a high quality, e.g. is correct and consistent [33]. However, data quality is context-dependent, which is why data providers often do not know what data quality is required by data consumers [34]. For this reason, on the one hand, there must be sufficient opportunities in the ecosystem for communication and feedback between data providers and the other actors, such as the analytics service providers, so that data quality can be continuously improved [16]. In some situations, it may also be useful to share poor quality data and let other actors or a crowd use and improve it [35]. On the other hand, all data-providing actors must be incentivized to provide high-quality data to the ecosystem. Higher quality data generally serves as a better basis for service providers' data-based analytics, who consequently can generate higher revenues with higher-quality data [13,8]. For this reason, among others, higher data quality is associated with higher monetary data value [22]. Based on this, it seems reasonable and necessary to incentivize high data quality within the data ecosystem, e.g. through monetary incentives. Compensating the effort for high data quality can also lead to network effects since a data set with a high quality has a higher chance to be used in the ecosystem and could also be relevant for several other actors [8].

4.3 Requirement 3: Establish trust

Another requirement for incentive mechanisms frequently mentioned in the literature is the establishment of trust. Trust is central to motivate actors to participate, e.g. by sharing their data in a data ecosystem [13,24].

On the one hand, this can be trust towards other actors in the ecosystem and for which purposes they will further use the shared data [36]. This is also often associated with trust in the technical infrastructure that is used for data sharing and the requirements it can fulfil, for example, with regard to data security and sovereignty. On the other hand, this can be trust in the actual shared data and its quality, as poor data quality can lead to significant damage in e.g. business processes [24]. These different types of trust in the data ecosystem can be established through a number of ways and methods. Firstly, these can be technical measures that regulate data security, data access, and data usage rights, for example, or track where data comes from and goes to [20]. This kind of trust can be established through the use of trust-building technologies, such as distributed architectures and ledger technologies, or through program verification and certification [9]. Secondly, trust can also be established through legal measures, such as contracts, or organisational and governance measures, such as joint agreements and rules for the ecosystem [37]. Another way to build trust in data ecosystems is to establish a trustee, such as a data fiduciary, who can serve as an independent intermediary between the ecosystem actors such as data providers and data consumers [9,38]. This concept is based, among other things, on a good reputation that the actors have towards this third party. In general, reputation is mentioned by some authors as another measure to build trust. For example, [39] introduce a blockchain-based infrastructure that allows data providers to be rated, which in turn can lead to data providers with better ratings being trusted more and vice versa.

4.4 Requirement 4: Foster sustainable ecosystem building

The data ecosystem concept is based on the idea of companies combining their individual offerings and data into an integrated solution that enables actors to create value through joint efforts [7]. Consequently, each actor hopes that the common goal is greater than the sum of its individual parts, and thus that they are better off by participating in the ecosystem than if they were alone [8,40]. For a functioning and sustainable data ecosystem, it must therefore be ensured that, on the one hand, each actor has an individual business model and a business strategy within the ecosystem and, on the other hand, that the ecosystem as a whole has common goals and value propositions [33,6]. Conversely, individual interests of the various actors and the complex relationships between them can lead to conflicting goals in the ecosystem [16]. For example, maximizing revenue for a data consumer may conflict with maximizing welfare for the entire ecosystem [8]. In addition, the ecosystem actors need to cooperate in some areas that do not directly add value or generate revenue, such as the joint development of standards for data models and interfaces [8,20]. Ultimately, a successful and sustainable data ecosystem must ensure that its members have a shared understanding of the ecosystem's operations and goals as well as that each actor is satisfied with its position in the ecosystem [41]. Sustainability in this context also means that the data ecosystem considers how it wants to develop further in the future and how, for example, new actors are accepted into the ecosystem. Depending on the structure and objective of the ecosystem, different decisions can be made in this regard [37].

4.5 Requirement 5: Avoid free-riders

Another category identified in the literature deals with hitchhiking and free-riders. Analogous to the sharing of other material or immaterial goods, the problem of free riding can also be observed in the sharing of data. This can be explained, on the one hand, by the fact that data sharing can result in the loss of exclusive control over the data, and opportunism on the part of competitors can inflict great losses on the sharing parties [42]. On the other hand, analogous to other forms of cooperation between companies, spillover effects can also be expected in data ecosystems [43]. These two circumstances can reduce the willingness of companies to share their data with others and instead encourage free-riding. For these reasons, incentive mechanisms must address and prevent excessive selfish behaviour by actors and promote truthfulness [33,8]. This is particularly relevant for alliance-driven and emerging data ecosystems, as these ecosystems can only function if several actors make contributions in the form of investments, for example [9,20]. In addition, the ecosystem community should consider how to deal with free-riders or even harmful behaviour and under what circumstances actors can be excluded from the ecosystem.

5. Conclusion

Using a structured literature review, we identified requirements for incentive mechanisms in industrial data ecosystems in this paper. The analysis of the existing literature has shown that some papers have already dealt with incentive mechanisms in data ecosystems. However, authors often focus only on single aspects, such as technical matters or specific domains. To the best of our knowledge, there is no previous work that provides a comprehensive overview of these different approaches in the form of requirements as it has been done in this paper.

From our results, we can derive several implications for theory and practice. In terms of **scientific contributions**, our work firstly contributes to a deeper general understanding of the emerging and still unexplored research field around industrial data ecosystems. In addition, the systematic description of the requirements aims to expand the existing body of knowledge about incentive mechanisms in data ecosystems and to contribute to the specification of a common understanding of these complex issues. In addition, our results can help in the development of incentive mechanisms and thus be the basis for methods for the sustainable building of data ecosystems that have not yet been explored in the literature [16].

Furthermore, the results of our paper provide multiple **contributions for practitioners**. First, the results can be used by organisations to understand the incentive mechanisms in the data ecosystems in which they are already involved. A better understanding of these issues could help practitioners shape the incentive mechanisms, and thus the data ecosystem, to their advantage and ultimately generate greater value from them. Second, the results of this study can help organisations and communities to build and design data ecosystems along with their incentive mechanisms, with the goal of realizing the benefits of sharing data across organisations [9].

The results of our study are, naturally, subject to certain **limitations** which should be taken into account when interpreting them. First, the identified requirements are based on an analysis of the scientific literature on industrial data ecosystems by the author team making the data search and analysis itself subject to interpretation. Consequently, other researchers might derive different results depending on their individual influences, preferences, and predilections. In addition, consideration of practice-based insights, such as those gained in case studies, could validate or extend the paper findings. Second, it should be noted that due to the constant technological progress and the still small number of studies, the concepts and understanding around industrial data ecosystems and incentive mechanisms are constantly evolving [15]. Lastly, the lack of a clear understanding and commonly accepted definition of data ecosystems makes it difficult to distinguish between related ecosystem concepts, e.g. platform ecosystems and other related forms of collaboration, such as corporate alliances or business networks [16].

However, the above-mentioned limitations indicate opportunities for **future research** topics. A possible next step would be to analyse how the requirements described can be implemented in practice. For this purpose, some of the requirements described should be examined in greater depth and their implementation options analysed. For example, it could be investigated in more detail how trust can be established in practice via technologies and how these can be implemented, or how trust can be measured in an ecosystem [9]. In general, building on the identified requirements and following related research topics, we see the development of design principles that support practitioners in the systematic implementation of incentive mechanisms for industrial data ecosystems as a next useful research avenue.

References

[1] Zolnowski, A., Christiansen, T., Gudat, J., 2016. Business Model Transformation Patterns of Data-Driven Innovations, in: Proceedings of the 24th European Conference on Information Systems.

[2] Davenport, T.H., 2013. Analytics 3.0. Harvard Business Review 91 (12), 64–72.

[3] Lis, D., Otto, B., 2020. Data Governance in Data Ecosystems - Insights from Organizations, in: AMCIS 2020 Proceedings.

[4] Oliveira, M.I.S., Lóscio, B.F., 2018. What is a data ecosystem?, in: Proceedings of the 19th Annual International Conference on Digital Government Research, Delft, Netherlands.

[5] Thomas, L.D.W., Autio, E., 2015. The processes of ecosystem emergence. AMPROC.

[6] Prieëlle, F. de, Reuver, M. de, Rezaei, J., 2020. The Role of Ecosystem Data Governance in Adoption of Data Platforms by Internet-of-Things Data Providers: Case of Dutch Horticulture Industry. IEEE Trans. Eng. Manage., 1–11.

[7] Priego, L.P., Osimo, D., Wareham, J., 2019. Data sharing practice in Big Data ecosystems. Esade Working Paper Nº 273, 38 pp.

[8] Badewitz, W., Kloker, S., Weinhardt, C., 2020. The Data Provision Game: Researching Revenue Sharing in Collaborative Data Networks, in: 22nd Conference on Business Informatics (CBI), Antwerp, Belgium, pp. 191–200.

[9] Cappiello, C., Gal, A., Jarke, M., Rehof, J., 2019. Data Ecosystems: Sovereign Data Exchange among Organizations: Report from Dagstuhl Seminar 19391. Dagstuhl Reports 9 (9), 66–134.

[10] Bundesministerium für Wirtschaft und Energie (BMWi), 2020. Kollaborative datenbasierte Geschäftsmodelle: Collaborative Condition Monitoring – Wie durch unternehmensübergreifende Kollaboration Mehrwert generiert werden kann.

[11] Yates-Mercer, P., Bawden, D., 2002. Managing the paradox: the valuation of knowledge and knowledge management. Journal of Information Science 28 (1), 19–29.

[12] Curry, E., 2016. The Big Data Value Chain: Definitions, Concepts, and Theoretical Approaches, in: Cavanillas, J.M., Curry, E., Wahlster, W. (Eds.), New Horizons for a Data-Driven Economy. Springer International Publishing, Cham, pp. 29–37.

[13] Azkan, C., Iggena, L., Möller, F., Otto, B., 2021. Towards Design Principles for Data-Driven Services in Industrial Environments, in: Proceedings of the 54th Hawaii International Conference on System Sciences, Hawaii, USA, pp. 1789–1798.

[14] Attard, J., Orlandi, F., Auer, S., 2017. Exploiting the Value of Data through Data Value Networks, in: Proceedings of the 10th International Conference on Theory and Practice of Electronic Governance - ICEGOV '17, pp. 475–484.

[15] Gelhaar, J., Groß, T., Otto, B., 2021. A Taxonomy for Data Ecosystems, in: Proceedings of the 54th Hawaii International Conference on System Sciences, Hawaii, USA.

[16] Oliveira, M.I.S., Barros Lima, G.d.F., Lóscio, B.F., 2019. Investigations into Data Ecosystems: a systematic mapping study. Survey Paper. Knowledge and Information Systems.

[17] Gröger, C., 2021. There Is No AI Without Data: Industry Experiences on the Data Challenges of AI and Call for a Data Ecosystem for Industrial Enterprises. Communications of the ACM, to appear.

[18] Moore, J.F., 1993. Predators and Prey: A New Ecology of Competition. Harvard Business Review 71 (3), 75–86.

[19] Azkan, C., Iggena, L., Gür, I., Möller, F.O., Otto, B., 2020. A Taxonomy for Data-Driven Services in Manufacturing Industries, in: Proceedings of the 24th Pacific Asia Conference on Information Systems (PACIS).

[20] Gelhaar, J., Otto, B., 2020. Challenges in the Emergence of Data Ecosystems, in: Proceedings of the 24th Pacific Asia Conference on Information Systems (PACIS).

[21] Spiekermann, M., Wenzel, S., Otto, B., 2018. A Conceptual Model of Benchmarking Data and its Implications for Data Mapping in the Data Economy, in: Multikonferenz Wirtschaftsinformatik (MKWI). Data driven X - Turning Data into Value, pp. 314–325.

[22] Otto, B., 2015. Quality and Value of the Data Resource in Large Enterprises. Information Systems Management 32 (3), 234–251.

[23] Prüfer, J., 2020. Competition policy and data sharing on data-driven markets: Steps towards legal implementation. Friedrich-Ebert-Stiftung, Bonn.

[24] Azkan, C., Möller, F., Meisel, L., Otto, B., 2020. Service Dominant Logic Perspective on Data Ecosystems - A Case Study based Morphology, in: Proceedings of the 28th European Conference on Information Systems (ECIS).

[25] Shen, M., Duan, J., Zhu, L., Zhang, J., Du, X., Guizani, M., 2020. Blockchain-Based Incentives for Secure and Collaborative Data Sharing in Multiple Clouds. IEEE J. Select. Areas Commun. 38 (6), 1229–1241.

[26] Webster, J., Watson, R.T., 2002. Analyzing the past to prepare for the future: Writing a literature review. MIS Quarterly 26 (2), xiii–xxiii.

[27] vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., Cleven, A., 2009. Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process, in: Proceedings of the 17th European Conference on Information Systems, Verona, Italy.

[28] Elsevier, 2020. Content - How Scopus Works. https://www.elsevier.com/solutions/scopus/how-scopus-works/content.

[29] Arnaut, C., Pont, M., Scaria, E., Berghmans, A., Leconte, S., 2018. Study on data sharing between companies in Europe, Luxembourg.

[30] Lacity, M.C., Khan, S., Yan, A., Willcocks, L.P., 2010. A review of the IT outsourcing empirical literature and future research directions. Journal of Information Technology 25 (4), 395–433.

[31] Glaser, B.G., Strauss, A.L., 1967. The discovery of grounded theory: Strategies for qualitative research. Aldine, New York, USA.

[32] Oliveira, L., Zavolokina, L., Bauer, I., Schwabe, G., 2018. To Token or not to Token: Tools for Understanding Blockchain Tokens, in: Proceedings of the Thirty Ninth International Conference on Information Systems (ICIS2018), San Francisco, USA.

[33] Al-Zahrani, F.A., 2020. Subscription-Based Data-Sharing Model Using Blockchain and Data as a Service. IEEE Access 8, 115966–115981.

[34] Fernandez, R.C., Subramaniam, P., Franklin, M.J., 2020. Data market platforms. Proc. VLDB Endow. 13 (12), 1933–1947.

[35] Freitas, A., Curry, E., 2016. Big Data Curation, in: Cavanillas, J.M., Curry, E., Wahlster, W. (Eds.), New Horizons for a Data-Driven Economy. Springer International Publishing, Cham, pp. 87–118.

[36] Rantanen, M.M., Koskinen, J., 2020. Respecting the Individuals of Data Economy Ecosystems, in: Cacace, M., Halonen, R., Li, H., Orrensalo, T.P., Li, C., Widén, G., Suomi, R. (Eds.), Well-Being in the Information Society. Fruits of Respect, vol. 1270. Springer International Publishing, Cham, pp. 185–196.

[37] Lis, D., Otto, B., 2021. Towards a Taxonomy of Ecosystem Data Governance, in: Proceedings of the 54th Hawaii International Conference on System Sciences, Hawaii, USA, pp. 6067–6076.

[38] Delacroix, S., Lawrence, N.D., 2019. Bottom-up data Trusts: disturbing the 'one size fits all' approach to data governance. International Data Privacy Law.

[39] Singh, P.K., Singh, R., Nandi, S.K., Nandi, S., 2020. Designing a Blockchain Based Framework for IoT Data Trade, in: Rautaray, S.S., Eichler, G., Erfurth, C., Fahrnberger, G. (Eds.), Innovations for Community Services, vol. 1139. Springer International Publishing, Cham, pp. 295–308.

[40] Gawer, A., Cusumano, M.A., 2014. Industry Platforms and Ecosystem Innovation. J Prod Innov Manag 31 (3), 417–433.

[41] Adner, R., 2017. Ecosystem as Structure. Journal of Management 43 (1), 39–58.

[42] Ji, G., Yu, M., Tan, K.H., 2020. Cooperative Innovation Behavior Based on Big Data. Mathematical Problems in Engineering, 1–14.

[43] McBride, K., Olesk, M., Kütt, A., Shysh, D., 2020. Systemic change, open data ecosystem performance improvements, and empirical insights from Estonia: A country-level action research study. Information Polity 25 (3), 377–402.

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