Data economy through productization: A conceptual paper

Sunday Adewale Olaleye, Jamk University of Applied Sciences, School of Business, Jyväskylä, Finland.
Akwasi Gyamerah Adusei, Industrial Engineering and Management, University of Oulu, Oulu, Finland.

Abstract
Start-ups and most SMEs who may not have the capacity to collect data by themselves can get an excellent foundation to grow their businesses due to access to the data marketplace. Companies utilize these data to generate insight to have an efficient business process and other business decisions. The rising potential and monetary value of data necessitates a quick solution and breakthrough to counter these problems associated with selling and buying data. Despite the insights from scholarly literature, the confluence of data economy and productization is not yet evident in the literature. This study intends to probe into this hanging issue. This conceptual research is conducted by observing and analysing secondary data on the data economy and productization. The methodology employed in this study dwells on library search and evaluation of previous literature reviews on data economy and productization. This study added to the existing contribution by extending the TTF theory to conceptualize data economy and productization. The study gave theoretical and managerial implications and stated the study's limitations and future research direction.

Keywords: *Data Economy, Productization, Data Platforms, The Task-Technology Fit*

Introduction

Statista (2022) has projected that Big Data globally in 2025 will reach 68 billion US dollars while the volume of data created will be tantamount to 181 zettabytes. These statistics established the potential of data market and how data has been described as a gold of this century. Data is playing a multidimensional purpose in the digital and sharing economy and its awareness, penetration, adoption, and governance is imperative (Shen, 2022). In today's era of rising digitalisation, data and information has become a very important resource for both the society and businesses (Stah et al. 2014; Li et al. 2015). The economic success and sustainability of most companies and businesses are highly dependable on the amount of data and information they have, as through data, companies can create new digital services as well as new business models (Otto & Österle, 2015). Start-ups and most SMEs who may not have the capacity to collect data by themselves are able to get a good foundation to grow their businesses due to access to data marketplace. In addition to that, AI professionals are also able to train various algorithms based on data (Falck & Koenen, 2020).

The economic relevance of data has become increasingly important. Kontroumpis et al. (2017) for example reported that 70% of large companies in 2015 bought data and was expected to rise to 100% in the year 2019. This implies data selling companies also continue to generate money through selling of their data. Falck & Koenen (2020) added to these statistics to buttress the economic relevance of data. According to the writer, 283000 companies in Europe were categorised as data providers in 2018 whose duty was just to provide data-based services and products. As of 2018, the number of companies has risen by 4.3% compared to 2017. In like manner, data employees had risen from 6.6 million in 2017 to 7.2 million by the year 2018. According to Bertoncello et al. (2016), the prospects derived from car generated data alone on a global scale overall creates a revenue of USD 450 billion and is projected to be about USD 750 billion by the year 2030. However, with all the rising figures, there was still high demand for data experts as about 571,000 vacancies still existed in the data companies only in the EU.

The rapid increase of data (Li et al. 2015) has become possible through various data sources including enterprise applications and other business IT, mobile computing, and Internet of things (IoT) devices (Fricker & Maksimov 2017), data generated from user transactions such as usage patterns and transactions and cookies from websites (Falck and Koenen,2020). However, amidst all the strategic assets data is, coupled with its economic benefit, data is still not fully harnessed to serve businesses. (Harkonen et al. 2019)

Data like any other physical product has great financial value (Harkonen et al. 2019). Companies utilize these data to generate insight that enables them to have an efficient business process and other business decisions. Data also facilitates the development of other new products and services as well as information problems are also reduced through data (Falck and Koenen, 2020). It could be sold in its raw form or as a processed data to organisations and other stakeholders. In that regard data is not only seen as an enabler of a product, but as a product itself. (Spiekermann et al. 2018).

Despite the economic value data provides, there are still several data selling challenges (Zhao et al. 2019). For example, on the customer side, the potential value of data is not fully recognised because data is not disclosed to buyers prior to purchase. (Spiekermann et al. 2018). Also, Spiekermann et al. (2018) added that, data providers or data sellers have issues with trust and security because of the fear that competitors could take advantage of the in-house data disclosed. Langdon & Sikora (2019), highlighted one key data value related challenge to be around data analytics. In the data analytics project, about 80% of time is spent on data wrangling alone. (Vollenweider, 2016). Recent authors also probe into knowledge accumulation, privacy, and growth in data economy (Cong, Xie & Zhang, 2021) while Hummel, Braun & Dabrock, (2021) gave reflection on data ownership. Despite the insights from scholarly literature, it is not yet clear in the literature the confluence of data economy and productization. This study intends to probe into this hanging issues and attempt to answer the following research question: 1) How can the integrated data task technology fit model impact the data economy? The second part of this study explained the economic relevance of data, while the third part conceptualised productization in the context of data economy. The fourth part summarised extant literature on data economy, productization and integrating the theory of the task-technology fit. The fifth part introduced the methodology to the study and the last part concluded the study with theoretical and managerial implications.

Economic relevance of data

Seeing the rapidly rising potential and monetary value of data necessitates a quick solution and breakthrough to counter these problems associated with selling and buying of data. Proper productization is one way to deal with these problems because data productization will help clarify the data offering and the proper measurement of data (Glassberg, 2018). Different researchers have attempted to develop some framework for creating economic value for data in literature. For example, Opher et al. (2016) studies on "The rise of the data economy: driving value through internet of things data monetization" mentioned that the data economy marketplace consists of data presenters, data insight providers, data platform owners, and data providers. Falck and Koenen (2020) also illustrates data value chain as the process flows from data collection, data analysis and then to the data actors who generate value. Another interesting study is by Zhao et al. (2019) who attempted to provide a solution to three major problems including data availability verification for customers, data providers privacy and payment fairness in the big data market. Zhao et al. (2019) proposed the solution through a "new blockchain-based fair data trading protocol".

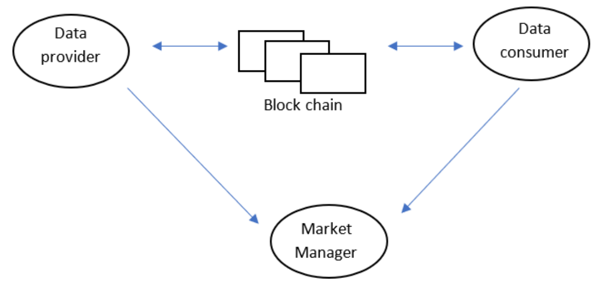

Figure 1. Blockchain-based data trading model in big data market. (Modified from Zhao et al. 2019).

From Fig.1 the market manager sets the platform which brings together both the data provider and the data consumer through registration. The data provider makes available his published topics of the data on the block after paying a deposit to the market manager. Data consumer then makes requests of data from the provider. Provider responds by sending encrypted data to the consumer. The customer then verifies by randomly challenging some blocks of data and the data provider then responds. If the customer is satisfied, he can now proceed with the purchase process. After purchase is done the customer receives a DAPS signature from the data provider to be able to decrypt the data. Finally, if the customer encounters a problem with the data, he can redeem his money back from the paid deposit from the data manager.

Data Productization

Anything that is available to be sold to a customer is classified as a product (Haines 2014). A product could be either tangible or intangible (Kahn 2012). All physical products are those referred to as tangible products whilst intangible products include software-based offerings, services (Hannila 2019).

Productization concept refers to the process of creating a product (Suominen et al. 2009). Productization creates a consistent logic of any product offering to all stakeholders (Harkonen et al 2018a). Harkonen et al. (2015) defines productization as "*the process of analysing a need, defining, and combining suitable elements, tangible and/or intangible, into a product-like defined set of deliverables that is standardised, repeatable and comprehendible"* A product structure provides the basics with which productization logic is found (Adusei et al. 2021, Lahtinen et al 2019). Through a product structure, a company's products are modelled (Sudarsan et al. 2005). Product structure shows the product, its data, components, and the relationship between them (Saaksvuori and Immonen 2008).

A product structure model according to Harkonen et al (2017) is divided into commercial product structure and

Table 1. Summary of selected literature on data economy and productization

Article title	Authors	Notable variables	Utilized Methodology	Findings	Study Limitations
Data Economy Literature					
The data economy: How technological change has altered the role of the citizen-consumer	Minna Lammia, Mika Pantzar	Data Citizen Data Democracy Citizen Consumer Data Economy Acceleration	Review	The study reveals how the digital turn has given citizen-consumers new channels of operations, querying how technological change has influenced their everyday lives.	The study concentrated on the commercial rather than the political side of consumer citizenship.
Data Governance as the Enabler of the Data Economy	Barbara Engels	Data Governance Data Management Data Architecture	Conceptual	The study discovered that data is a strategic asset, it needs to be treated accordingly starting with proper data governance, which is a practice, not a project.	This study is only limited to data governance, data management and data architecture. Aspect of data productization was not considered in this study.
Skill discrepancies between research, education, and jobs reveal the critical need to supply soft skills for the data economy	Katy Börnera, Olga Scrivnera, Mike Gallanta, Shutian Maa, Xiaozhong Liua, Keith Chewning, Lingfei Wue, and James A. Evans	Publications data Courses Skill bursts Jobs	Survey The authors analysed skill networks and evaluate covarying time series of skills.	The study reveals the increasing importance of uniquely human skills, such as communication, negotiation, and persuasion. These skills are currently underexamined in research and undersupplied through education for the labor market. In an increasingly data-driven economy, the demand for "soft" social skills,	This study is limited to the ancillary of data economy in terms of skills development and human resources mobilization. This conceptual paper differed from this study by combining the data economy and productization.

				like teamwork and communication, increase with greater demand for "hard" technical skills and tools.	
The Personal-Data Tsunami And the Future of Marketing A Moments-Based Marketing Approach For the New People-Data Economy	SHAWN O'NEAL	People-Data Economy Human Anxiety Transparency	Viewpoint	The personal-data tsunami will be trans-formational for making better, faster, more targeted marketing investments, and for knowing in real time whether the investments are working.	This study is limited to investment on people's data that is, personal and social media information that is being collected every day. Every transaction that we as modern human beings are making in the world around us.
Productization Literature					
Productization and product structure enabling BIM implementation in construction	Solmaz Mansoori, Janne Harkonen and Harri Haapasalo	Productization, Product structure, Information management, BIM, Construction management	conceptual research and a single case study	A framework called Part-Phase Matric was designed. The framework is a product structure which is construction - specific and provides the platform for information consistency in BIM	The findings of the study are only limited to a single case and a conceptual study
Productization levels towards whole product in SaaS business	Teppo Yrjönkoski, Kari Systä	Software as a service, Productization, On premise business, Product management	Single case empirical research	A three-level phased based productization model namely proof of concept, Individual sales from 1st to 10th customer, mass distribution is created	The results have been based on the analysis of only one case company and therefore the model needs to be validated with several company analysis
Commercial and Technical	Niko Lahtinen, Erno Mustonen,	Key performance indicator, product	Qualitative single case study research	The main contribution is	Research findings are limited to a single case

Productization for Fact-Based Product Portfolio Management Lifecycle	Janne Harkonen	lifecycle management, commercial and technical productization, PPM targets		the creation a framework of productization over a product lifecycle as well as providing the best Product portfolio management targets and key performance indicators	company as well as certain product line divisions. A more variety of different industries needs to be analysed to validate the findings
Productization: Transforming from Developing Customer-Specific Software to Product Software	Peter Artz, Inge van de Weerd, Sjaak Brinkkemper, and Joost Fieggen	Productization, standardised product software, customer - specific software	Design science and case study research	The reveals a transformation from customer-specific software to product software through a six-stage proposed productization process	The study findings were based on a single case study, and therefore a more case studies are required to validate the findings
Developing a Product-Service System through a Productization Strategy: A Case from the 3PL Industry	Andrew Lahya, Ai Qiang Li, Pauline Found, Aris Syntetos, Mike Wilson, Nicole Ayiomamitou	Product Service Systems, productization,	Exploratory case study	This study shows the new driving and restraining forces to pursuing PSS, refines a conceptual framework that supports companies' decision making on PSS, creates an established methods on force field analysis	Search terms focused only on PSS and product service systems and therefore other homogenous terms should be considered in future research

technical product structure. The commercial product structure in a hierarchical level includes the solution level, product family level, product configuration level and the sales items level. The commercial product structure is visible to the customers. The technical product structure depending on whether it is tangible, or intangible is also hierarchically arranged. Technical product structure for tangible products includes, product version items, main assembly, sub-assembly, components. For intangible products, the technical product structure includes, version items, main process, sub process, cost drivers, resources.

Integrated Theoretical Framework of Data Task Technology Fit

The task-technology fit (TTF) theory states that information technology is more likely to improve individual performance and be employed if its capabilities match the tasks that the user must do (Goodhue and Thompson, 1995). *Quality, locatability, authorization, compatibility, ease of use/training*, production timeliness, systems reliability, and relationship with users are all variables in Goodhue and Thompson's task-technology fit assessment. Each aspect is assessed using two to ten questions, with responses ranging from strongly disagree to strongly agree on a seven-point scale. The interdependence between an individual (a technology user), technology (data, hardware, software tools, and the services they provide), and task (activity carried out by individuals to achieve the required output) features is referred to as task-technology fit. The degree to which technology can accomplish a user's activities is determined by how well individual abilities, task requirements, and technological features fit (Goodhue & Thompson, 1995).

Although the Goodhue and Thompson (1995) model focuses on the person, Zigurs and Buckland (1998) propose an equivalent model that focuses on the group. TTF has been utilised in a variety of information systems, including electronic commerce systems, since its inception, and has been coupled with or used as an extension of other models linked to IS outcomes, such as the technology acceptance model (TAM). The TTF measure proposed by Goodhue and Thompson (1995) has been modified multiple times to suit the needs of the study. This study integrates TTF into data economy and productization as data task characteristics, data platform characteristics, data technology task fit, data performance impacts and data utilisation.

Data Task Characteristics: Data has become an integral part of our society and it is present in our daily lives. This study inferred from the description of task characteristics amplified in the study of Spies, et al. (2020) and postulate that Data Task Characteristics are cognitive actions employed in processing data through different levels of tasks with the support of appropriate technology. The data task characteristics should be exemplified with the principle of FAIR data, that is, it should be Findable, Accessible, Interoperable and Reusable. Beyond these, it should be a quality data that is accurate, complete, reliable, relevant, and timely. This study hypothesized that (H1) Data Task Characteristics will positively contribute to the Data Task-Technology Fit in an organization.

Data Platform Characteristics: A data platform is a collection of technologies that work together to support an organization's end-to-end data demands. It allows you to acquire, store, prepare, deliver, and regulate your data, as well as provide a security layer for users and apps. A data platform is essential for maximizing the value of your data. Data Platform Characteristics are the different channel that an organization use to process their data and these platforms are in different categories. It could be enterprise data platform that caters for enterprise data assets. Enterprise Data Platform (EDP) could be Online Transactional Processing (OLTP) databases, data warehouses and data lake. Modern Data Platform evolves from Electronic Data Processing (EDP) and it accommodates the processing of structured, semi-structured and unstructured large scale data. It could be useful for organizations for developing Artificial Intelligence (AI), Machine Learning (ML) applications or Natural Language Processing (NLP). The dynamism of Cloud Data Platform is another interesting dimension. Organization can transfer or share the risk of their data storage and processing in real lifetime on the cloud to the Cloud Data Service Providers. The Cloud Data Platform can manage unlimited data storage, Massively Parallel Processing (MPP) Database and middleware that integrates them together. Big Data Platform is a specialised channel for data analytics. It can be used to integrate different big data tools and ensure the availability, security, performance, and scalability of the data. Further, Customer Data Platform (CDP) relies on customer-related data. It combines different sources of data such as social media, websites, Customer Relationship Management (CRM), electronic commerce and digital advertising data for analysis and insights. This study hypothesized (H2) that using a scale of preference to order different data platforms based on their characteristics in an organization will contribute to the Data Task-Technology Fit.

Data Technology Task Fit: Technology is often used in an organisation to generate value by improving or supporting individual and group work, but it does take a lot of resources to acquire, deploy, and use the various technologies. Whenever the employed technology (data platform, data analysis tools) fits the data task characteristics it intends to support, the end results is Data Performance Impacts. These impacts could be revenue per customer, customer retention rate, customer satisfaction and revenue growth. This study hypothesized (H3) that Data Task-Technology Fit will metamorphosise into Data Performance Impacts and contribute to organizational revenue, customer retention, satisfaction, and growth.

Data Utilisation: Organization needs data for insights, decision making and revenue. This study hypothesized (H4) that Data Task-Technology Fit will create value for Data Utilization through data productization and data monetization.

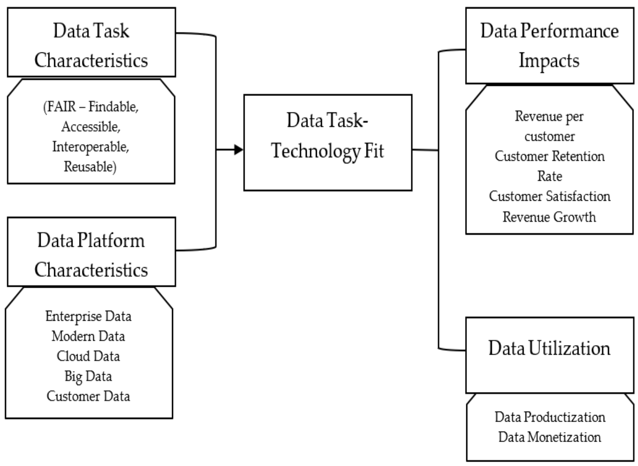

Figure 2. Integrated Theoretical Framework of Data Task Technology Fit

Methodology

This conceptual research is conducted through observation and analysis of secondary data on the data economy and productization. The methodology employed in this study dwells on library search and evaluation of previous literature reviews on data economy and productization. The study starts with topic selection and refinement based on the prior understanding of the authors of the research domain of data economy. Second, the authors gathered relevant literature. The library search is a combination of online and offline that constitutes academic journals, conference proceedings, book chapters, white papers, and reports. References for this study emanate from databases such as Web of Science, Scopus, and Google Scholar. The search begins with Google Scholar and is complemented by the Web of Science and Scopus. The searches on the databases are limited to data economy, productization, data platforms, and task technology fit. Third, the authors identified specific variables for the study. Fourth, the authors generate the framework by using the mix of variables from the scientific articles and other crucial materials consulted. The proposed framework helps to reduce the knowledge gap.

Productization through data product structure model

Figure 3 shows a proposed data product structure model adopted from Harkonen et al 2019. From the commercial data product structure, the data solution level shows the broader data sector. Under the data sector could be found the different data categories, for example category 1, 2 or 3 could be health data, legal data, real estate data respectively. Each data category forms a separate data product family. At the data product configuration level, each product category could have different data specific types that meet the needs of the customer. Customers may make their preferences from the list of the data sales items. It is crucial to note that the sales items level is the last stage of the commercial data structure. The sales items level may have a list of data specifics that may be optional or compulsory to choose from. In addition to the compulsory data, customers can choose from the list of optional sales data to form their data configuration that will serve their specific needs. Sellable data for example could be raw-data, processed data, or both. Only the commercial product structure is visible to the customers.

The technical product structure is the internal details that go on to arrive at the commercial product structure. These include the data version items, the data processes and sub-process, cost drivers and the resources needed. It should be noted that the price of each sales item includes the cost of the technical version item plus the profit.

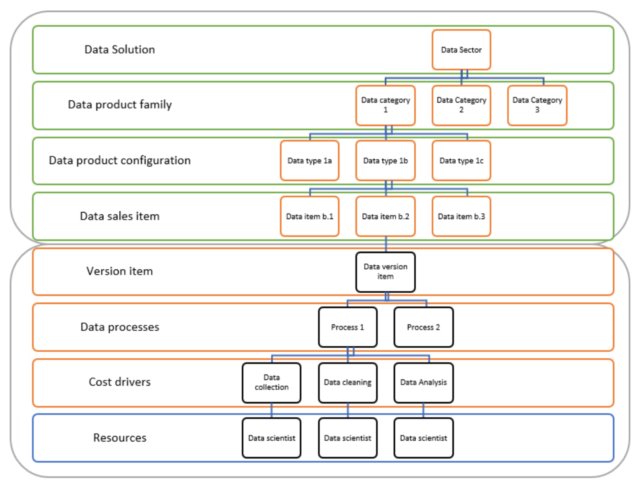

Figure 3. Commercial and technical data product structure

Conclusion

This study attempts to answer the hanging research question in the literature and shows that integrated data task technology fit model can positively impact the global digital ecosystem. Studies have without doubt revealed the economic relevance and value of data in the present digital economy and as a result, data like any other sellable products require careful attention to maximise its profitability and economic value. Also, the subject of productization has been much applicable in the scope of various tangible and intangible products, however, current literature has not yet clarified the link between data economy and productization though the economic value of data has been highly recognised in literature.

This study added to the existing contribution by extending the TTF theory to conceptualize data economy and productization. The main contribution of this study is to propose a data productization through a data product structure model. This study is very relevant as it complements the ongoing productization research (Harkonen et al. 2019) by extension in the data economy perspective. The productization through data product structure model proposed shows the commercial and technical productization in the hierarchical order and shows the relationship between the data structure.

Our research also reveals the applicability and the integration of data economy and productization in the Task technology fit framework as data task characteristics, data platform characteristics, data technology task fit, data performance impacts and data utilisation. The integration of TTF theory is consistent with the study of Wang, Luo & Yu, (2022) as the authors integrate TTF theory with IoT technology.

Theoretical and Managerial Implications

Prior to this study, Spies, Grobbelaar & Botha, (2020) confirmed that TTF theory has been applied in different research domain and emphasised on healthcare and mobile technology. This study forms a new conceptualization of data economy and productization with an integrated framework of TTF theory. This study is very relevant and applicable to data product managers and the entire data monetisation and industry. Data managers can get a better grip on their data management as the results of this study provides the needed tool and platform needed for effective data management to obtain maximum profitability. The data product structure shows the holistic data structure and portfolio as well as clarifying the data offering by providing a better picture to all data stakeholders such as data buyers, data sellers and data platform managers.

Limitations and Future Study

Our study is not without limitation especially considering the emerging research scope like data economy and productization. Our study is conceptual research, and the findings are based on the analysis of secondary data through a literature review and a library search. The need for further research through empirical research in a case company where real case data products can be studied and productization concept applied is highly recommended. Also, the future researcher should endeavour to empirically test the four hypotheses proposed in this study. The future researcher should also test the proposed integrated Theoretical Framework of Data Task Technology Fit quantitatively and the proposed commercial and technical data product structure should be tested practically in different organisations across the borders.

Citation
Olaleye, S.A; Adusei, G.A, (2022). Data economy through productization: A conceptual paper. In Proceedings of the 29th International Management Development Association (IMDA), pp. 68-76.

Acknowledgement
This work was supported by the Foundation for Economic Education (Liikesivistysrahasto), Finland [grant number: 16-9388], [grant number: 18-10407], [grant number: 20-11445], [grant number: 20-11046].

References

Adusei, A. G., Härkönen, J., & Mustonen, E. (2021). Productization and product structure: Extending the perspective to software business. *International Journal of Business and Administrative Studies, 7*(2), 89-106.

Artz, P., Weerd, I.V.D., Brinkkemper, S. and Fieggen, J., 2010, June. Productization: transforming from developing customer-specific software to product software. *In International Conference of Software Business* (pp. 90-102). Springer, Berlin, Heidelberg.

Bertoncello, M., Camplone, G., Gao, P., Kaas, H.W., Mohr, D., Möller, T. and Wee, D., 2016. Monetizing car data—new service business opportunities to create new customer benefits. McKinsey & Company, pp.1-60.

Cong, L. W., Xie, D., & Zhang, L. (2021). Knowledge accumulation, privacy, and growth in a data economy. *Management Science*, 67(10), 6480-6492.

Falck, O., & Koenen, J. (2020). Resource" Data": Economic Benefts of Data Provision. *In CESifo Forum* (Vol. 21, No. 03, pp. 31-41). München: ifo Institut-Leibniz-Institut für Wirtschaftsforschung an der Universität München.

Fricker, S. A., & Maksimov, Y. V. (2017, June). Pricing of data products in data marketplaces. *In International Conference of Software Business* (pp. 49-66). Springer, Cham.

Glassberg Sands, E. (2018). How to build great data products. In: Harvard Business Review. https://hbr.org/2018/10/how-to-build-great-data-products

Goodhue,Dale L., "Understanding user evaluations of information systems", *Management Science*, 1995, 41, 12, 1827-1844.

Goodhue,Dale L.;Thompson,Ronald L., "Task-technology fit and individual performance", *MIS Quarterly*, 1995, 19, 2, 213-236.

Haines, S. (2014). Product manager's desk reference. New York, NY: McGraw-Hill Education

Hannila, H., Tolonen, A., Harkonen, J., & Haapasalo, H. (2019). Product and supply chain related data, processes and information systems for product portfolio management. *International Journal of Product Lifecycle Management*, 12(1), 1–19.

Harkonen, J., Haapasalo, H., & Hanninen, K. (2015).

Productisation: A review and research agenda. *International Journal of Production Economics*, 164, 65–82.

Harkonen, J., Mustonen, E., & Hannila, H. (2019). Productization and product structure as the backbone for product data and fact-based analysis of company products. *In IEEE International Conference on Industrial Engineering and Engineering Management (IEEM)*, Macao, China (pp. 474–478).

Harkonen, J., Tolonen, A., & Haapasalo, H. (2017). Service productisation: Systematising and defining an offering. *Journal of Service Management*, 28(5), 936-971

Harkonen, J., Tolonen, A., & Haapasalo, H. (2018a). Modelling of manufacturing services and processes for effective productization. *In 20th International Working Seminar on Production Economics*, Innsbruck, Austria (p. 19-23).

Hummel, P., Braun, M., & Dabrock, P. (2021). Own data? Ethical reflections on data ownership. *Philosophy & Technology*, 34(3), 545-572.

Kahn, K. B. (2012). The PDMA handbook of new product development. New York, NY: John Wiley & Sons.

Koutroumpis, P., Leiponen, A., & Thomas, L. D. (2017). The (unfulfilled) potential of data marketplaces (No. 53). *ETLA Working Papers*.

Lahtinen, N., Mustonen, E. and Harkonen, J., 2019. Commercial and technical productization for fact-based product portfolio management over lifecycle. *IEEE Transactions on Engineering Management*, 68(6), pp.1826-1838.

Lahtinen, N., Mustonen, E., & Harkonen, J. (2019). Commercial and technical productization for fact-based product portfolio management over lifecycle (just accepted). *IEEE Transactions on Engineering Management*, 1-13.

Lahy, A., Li, A.Q., Found, P., Syntetos, A., Wilson, M. and Ayiomamitou, N., (2018). Developing a product–service system through a productisation strategy: a case from the 3PL industry. *International Journal of Production Research*, 56(6), pp.2233-2249.

Langdon, C. S., & Sikora, R. (2019, December). Creating a Data Factory for Data Products. *In Workshop on E-Business* (pp. 43-55). Springer, Cham.

Li, J., Tao, F., Cheng, Y., & Zhao, L. (2015). Big data in product lifecycle management. The *International Journal of Advanced Manufacturing Technology*, 81(1), 667-684.

Mansoori, S., Harkonen, J. and Haapasalo, H., 2022. Productization and product structure enabling BIM implementation in construction. Engineering, Construction and Architectural Management.

Opher, A., Chou, A., Onda, A., & Sounderrajan, K. (2016). The rise of the data economy: driving value through internet of things data monetization. IBM Corporation: Somers, NY, USA.

Otto, B., & Österle, H. (2015). Corporate data quality: Prerequisite for successful business models. epubli. product lifecycle management. *Computer-Aided Design*, 37(13), 1399–1411

Saaksvuori, A., & Immonen, A. (2008). Product lifecycle management. Berlin, Germany: Springer Science & Business Media.

Shen, Y. (2022). Data governance in China's platform economy. *China Economic Journal*, 1-14.

Spiekermann, M., Tebernum, D., Wenzel, S., & Otto, B. (2018). A metadata model for data goods. *In Multikonferenz Wirtschaftsinformatik* (Vol. 2018, pp. 326-337).

Spies, R., Grobbelaar, S., & Botha, A. (2020, April). A scoping review of the application of the task-technology fit theory. *In Conference on e-Business, e-Services and e-Society* (pp. 397-408). Springer, Cham.

Stahl, F., Schomm, F., & Vossen, G. (2014). The data marketplace survey revisited (No. 18). *European Research Center for Information Systems* (ERCIS) Working Paper.

Statista, (2022). Big data - Statistics & Facts. Retrieved from Big data - Statistics & Facts | Statista. Accessed on 14.05.2022.

Sudarsan, R., Fenves, S. J., Sriram, R. D., & Wang, F. (2005). A product information modeling framework for product lifecycle management. Computer-aided design, 37(13), 1399-1411.

Suominen, A., Kantola, J., & Tuominen, A. (2009). Reviewing and defining productization. *In 20th Annual Conference of the International Society for Professional Innovation Management* (ISPIM 2009), Vienna, Austria.

Vollenweider, M. (2016). *Mind+ Machine: A Decision Model for Optimizing and Implementing Analytics*. John Wiley & Sons.

Wang, H., Luo, X., & Yu, X. (2022). Exploring the role of IoT in project management based on Task-technology Fit model. *Procedia Computer Science*, *199*, 1052-1059.

Yrjönkoski, T. and Systä, K., 2019, August. Productization levels towards whole product in SaaS business. In *Proceedings of the 2nd ACM SIGSOFT International Workshop on Software-Intensive Business: Start-Ups, Platforms, and Ecosystems* (pp. 42-47).

Zhao, Y., Yu, Y., Li, Y., Han, G., & Du, X. (2019). Machine learning based privacy-preserving fair data trading in big data market. *Information Sciences*, *478*, 449-460.

Zigurs,Ilze;Buckland,Bonnie K., "A theory of task/technology fit and group support systems effectiveness", *MIS Quarterly*, 1998, 22, 3, 313-334.