Research Plan: Data as a Service dominates Data Economy and Monetization

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1 Background

1.1 Introduction to the research field

According to some scholars on-going digital transformation is already leading to major changes in established known value creation structures as well as traditional business models of companies (Weill and S. Woerner 2015; Yoo et al. 2010). One of the key drivers is data. Data are used to improve internal processes and as strategic fuel for data-driven innovations and business models (Zakari 2020; Zolnowski et al. 2016).

Economic value or innovations derived from data are less and less created by one organisation. Instead, we are witnessing is the dominance of cross-industry operating socio-technical networks – so-called data ecosystems (Hein et al. 2019; Oliveira and Lóscio 2018; Yoo et al. 2010). We are not only crossing the borders between companies, business segments or even borders between countries or continents, we are also crossing the border between humans and systems. What we are witnessing is the emergence of cybernized services, in which the human role in the service process is gradually replaced by digital systems (Tuunanen et al. 2019). Even in cybernized systems, data is at the core of the value creation.

Given the nature of data ecosystems requiring border crossing activities in value creation, data used in the process must be packaged into products for more efficient reuse and sales (Demchenko et al. 2018. Jedd et al state in Harvard Business Review that data should be approached with product mindset (Jedd et al. 2020). Value creation from data has traditionally fallen under data governance and it's time to update what we include in the data governance.

Data Governance Due to increasing importance of data, data governance is on the rise and it considered key requirement of the data economy (Engels 2019).

Multiple Data governance definitions can be found from the research literature. For example Cohen defines data governance as "*the process by which a company manages the quantity, consistency, usability, security, and availability of data*" (Cohen 2007). Newman and Logan define data governance as "*the collection of decision rights, processes, standards, policies, and technologies required to manage, maintain and exploit information as an enterprise resource*" (Newman and D. 2006). Weber et al. approach the data governance from data perspective and consider "*Data Governance as a structural framework for decision-making rights and responsibilities regarding the use of data in an enterprise*" (Weber et al. 2009). The multitude of aspects to data governance is extended with Khatri's and Brown 's approach to link enterprise's "data assets" and assignment of decision making rights. (Khatri and Brown 2010).

In the modern data governance we have both supply and value chain aspects with equal importance. Data supply chain feeds data pipelines for use in data products, which are the manifestations of data value chain. Creation, delivery and utilization are parts of the *data value chain* in which raw data is converted to more valuable asset and offered for value-creation as a service. Often the focus is on the data supply chain.

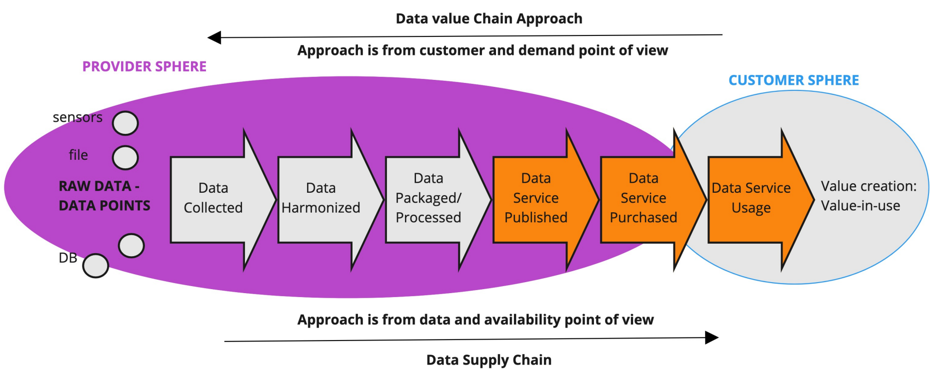

Figure 1: Simplified value chain with data supply and value chain aspects. Value creation aspects adopted from Grönroos (Grönroos 2011)

Yet there is a big difference between *data supply chain* and *data value chain*. Modern Data Governance must include both sides - data value chain and data supply chain. The data supply chain approach sees data as an asset while the data value chain approach treats data via value-creation point of view. The supply chain focuses on enabling data flow and security. The value chain focuses on customer needs, who uses the data, and what kind of value it creates. In short, the data supply chain has a governance focus while the data value chain has a business and customer focus. The focus in data value chain is transferred more towards the customer and away from the product.

Compared to Data Supply Chain described by Spanaki et al (Spanaki et al. 2016), my thinking is based on the idea that data value chain is built in parallel with data supply chain, but the approach is from customer point of view (see Fig 1). In addition to that, approach has adopted value creation described by Grönroos (Grönroos 2011. The roles of participants in the value chain are discussed in more details later in the document.

The outcome of the data value chain is Data as a Service (see Fig 1). Data as a Service driven offering is the manifestation and vessel of value in data value chain. Data is collected, refined, combined and wrapped with service-logic. Then data as a service is published and marketed. Eventually data as a service is purchased and consumed by customers which at the moment are often data scientists. At this point customer creates and evaluates the value gained.

1.2 Emerging data commoditization

At the same time with data governance renaissance data is increasingly becoming an article of trade or commerce - in short, a product (Engels 2019). The era of data is about the process of refining data or commoditization. At the same time data is becoming an independently valuable asset that is freely available and interchangeable on the market. (Gelhaar and Otto 2020; Möller et al. 2020; S. L. Woerner and Wixom 2015) A "commodity" is defined as something useful that can be turned to commercial or other advantage. Some well known examples of traditional commodities are grains, gold, beef, oil and natural gas. In brief, a commodity is a basic good used in commerce that is interchangeable with other commodities of the same type and are often used as inputs in the production of other goods or services.

Open data is the strong manifestation of this new era. The government mandates and open data policies from multiple countries and public entities continue to contribute to the process of data commoditization. Openness has the benefit of increasing the size of the market. The greater the size of the market and the demand for a resource, the greater the competitive pressure on price and, hence, the increase in commoditization of the resource.

Data as a Product was one step towards servitized data. Open data started the tsunami of data and after the hype data monetization and commercialization have raised the often discussed topics also in the academic research (Gelhaar and Otto 2020; Kaiser et al. 2019; Moro Visconti et al. 2018). Yet the focus has been mostly in big data and technical aspects of the data. Emerging data economy markets are not fully yet here yet. Instead we are still in the phase of learning to utilize and monetize data - both require data value streams which are expected to follow the service-driven paradigm more than goods-dominant paradigm.

1.3 From Products to Services

Data as a Product seems to be a topic from the past and paradigm change in eve larger scope towards service-driven offering has occurred. The data economy landscape has already changed. Data as a Service is the term that dominates the emerging data economy and is likely to be the foundation of the future data value streams. Using the term Data as a Product might sound outdated to some. Some of us want to approach the data economy from service-dominant logic point of view.

Before we take a deep dive into Data as a Service, it is fundamental to understand that other megatrends and business model trends affect data economy just like any other economy. In the context of this research two major trends to discuss are subscription economy and servitization.

1.3.1 Subscription Economy

One of the big changes that has already occurred is that we have entered Subscription Economy. The Subscription Economy is a phrase, coined by Zuora, describing the new business landscape in which traditional pay-per-product (or service) companies are moving toward subscription-based business models.

At the same time generations of people are less interested about owning. Younger generations do not want to buy a house with 30 years of payments, they rather not own cars or cottages. We no longer buy CDs or DVDs either (see Figure 2). Instead we subscribe to services which offer us the goods - both physical and digital. We are no longer paying to own - we are paying to get access.

To watch movies and tv-shows we are not buying the digital products or physical discs. We subscribe to Netflix of alike service. That way we get access to hundreds of movies and tv-series. Of course our favourite shows are part of different streaming services and we need to subscribe to both of them and in worst case more and more to multiple services.

1.3.2 Servitization

The above described service driven logic is not B2C specific. Products get wrapped around with services such as the customer experience and solution levers. Many products regardless of nature, hardware or software, are being offered ”as a service”. Term used to describe the phenomenon is servitization.

The same is reality in big scale between companies as well. In its simplest terms, servitization refers to industries using their products to sell “outcome as a service” rather than a one-off sale. The phenomenon of servitization is found beneficial not only with streaming media business but also in manufacturing. In servitization manufacturing businesses offers additional services to supplement their traditional product offering for example with maintenance and keeping a fleet of vehicles on the road as a service. Servitization is usually a subscription model and can be applied to most industries in one way or another. Jet engines

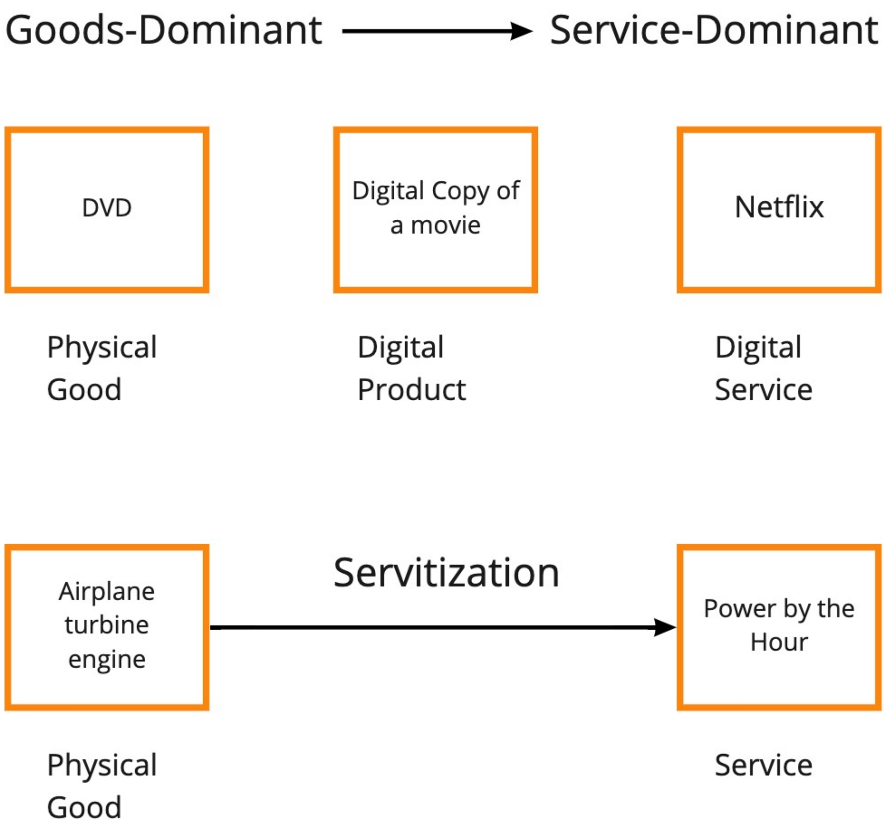

Figure 2: From goods to services

are sold as "Power by the Hour" (see Figure 2). The airline does not pay for the engines, but for the time they are flying. This model includes necessary services and for example data about the engines. This is a big change compared to the old jet engine landscape.

In data economy example is to provide updated situation as a stream of data just like we stream movies from Netflix. We are not interested to own the data, we want to consume it to create value for own purposes. With data instead of owning it, consumer wants to have rights to do something with it. Just like with APIs, which you do not buy to own, but to consume.

In the Data as a Service logic, the product might be there, but what is sold and purchased is the service. Furthermore, the data as a product is not always even present since it's just data stream. Limitations of usage, pricing, name and all that traditional business logic is in the service instead. The change has been noticed and expained also by the academic community. What we are witnessing is the age of service-dominant logic.

1.4 The age of service-dominant logic

An academic article by Stephen Vargo and Robert Lusch (Vargo and Lusch 2004) from 2004 about new service-dominant logic fuelled a truly international discussion about the potential of service logic to change the mainstream, goods-based logic. The authors conclude that "*perhaps the central implication of a service-centered dominant logic is the general change in perspective*" (Vargo and Lusch 2004). Here are a few selected aspects of the service-dominant logic.

Firstly, service-dominant logic is a perspective for understanding value creation. Value creation in turn is at the core of practically any business. The goal of service systems is to provide input into the value-creating process of other service systems. All involved parties should gain some value. The firm gains for example financial benefits and customer value in terms of becoming "better off" in some way.

Secondly, in service-dominant logic, the customer is actively participating in the value creation. Customer is not an object, but an active subject - one source of value creation. The customer is always a co-creator of value and is always involved in the value-creation process. According to some scholars, the customer is the primary creator and evaluator of value. The service provider could be invited to join this process as a co-creator. Without the customer, goods or services have no value except negative due to related costs.

Thirdly, the firm is fundamentally a value facilitator. The service approach focuses on interactions instead of exchange. The producer is not so much trying to match the customer's expectations in advance which is a must-have in product-dominant logic. Instead, the service provider is not restricted to offering value propositions only but also can directly and actively influence customers' value fulfillment in some situations.

Lastly, service is more about the process than the result. According to research goods are a distribution mechanism for service provision (Kowalkowski 2010; Svensson and Grönroos 2008). Goods have no value in themselves, but only as transmitters of service for the user. As an example razor provides service which previously was offered by barbers. Goods are one of several types of resources functioning in a service-like process, and it is this process that is the service that customers consume. Instead of luring consumers to the exchange process, the old goods-based, we are geared towards facilitating interaction.

Given the above, the claim included in Service-Dominant Logic is that it is all about service. We are living in the Subscription economy and services are eating the world. Thus the selected viewpoint to data monetization in this research is Data as a Service.

1.5 Data as a Service

Now turn your head towards the data economy. Keep the things in mind we just discussed. Figure 3 is suggested framework of the data as a service landscape. The drawing is focused on data monetization and how to do that. It is built upon the level of data servitization and publicity of the service. Of course, the real world is not this simple and diffusion between the publicity levels occurs. The drawing is intentionally drawing your focus on the service by leaving products out of it.

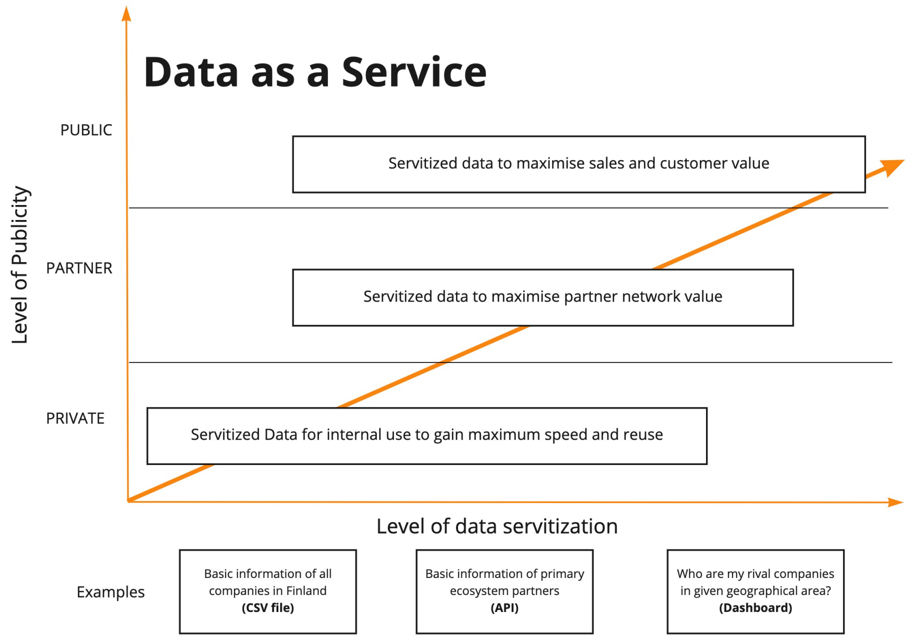

Figure 3: Data as a Service

The publicity levels have been taken from the API Economy in which over time such layers have been found to include practically all commercial APIs. Data as a Service and APIs share a lot of features and thus the categories are expected to apply to Data as a Service logic as well. Furthermore, in the data as service logic, APIs are expected to have significant role Spanaki et al. 2016. The number of new available Web APIs that give public access to data started growing explosively around the beginning of the era of data. APIs have become the plumbing for data economy mostly because data is more and more created by devices and sensors and intended as digital fuel rather than end product. Thus it is justified to say that emerging data economy requires both servitized APIs and data to succeed. When you combine APIs and data, you are offering data as a service. Data harmonizing platforms such as Platform of Trust contain servitized APIs as well as data source system integration and thus handles the plumbing for your data value chain. In short, platform is acting as Data as a Service enabler.

In the lowest level of servitization is data which is servitized to gain speed and increase reuse and usability. Currently, according to a survey data scientists use 45% of their time to prepare data for later use[1]. Servitizing the data will decrease the time needed for processing it. Data at this level of publicity and servitization is intended mainly for internal use.

Consuming internally your data as a service does not sound like something to take a big role now. But in the network layer, for example, ecosystem partners, it makes sense it servitize data for them and the result is Data as a Service. In some cases, data in almost raw unprocessed format is provided for partners. Such an example is warehouse management. The technical means to offer data as a service might be API.

Offering raw data for the public 3rd party consumption does not make sense. Selling your raw material results in a lower value for the company and customers often lack the necessary resources to process and refine the data for the value they aim for. At this highest level of publicity and servitization, data is often not even recognizable but visualized as graphs or even as functions answering questions and creating inputs for other systems.

In short, from provider firm's point of view, we can say that you need to servitize data for internal use to gain maximum speed, you need to servitize data to maximize partner network value and you need to servitize data to maximize sales and customer value.

In the research focus is on the data value chain and *Data as a Service* concept. Less focus on put on the data supply chain and governance oriented asset approach. Data monetization is the process by which businesses create revenue from their data, which are offered as Data as a Service for consumers.

1.6 Motivation

Motivation for the topic (Why is it important?)

We are now transiting from collecting data to analyzing it for internal benefits. That is an ongoing process already in global level. What is expected to happen after that is data monetization outside own organisation in form of selling Data as a Service. To achieve that we need to apply customer focused process to data servitization. The process most likely has to be lean and design driven to min-

[1]https://www.anaconda.com/state-of-data-science-2020

imize waste and have built-in validation from customer before implementation. Currently there are no tools nor clear process model for this purpose.

Many have argued that the competition in the markets has evolved from competition between individual companies to a competition between connected operations forming supply chains (see for example Whipple and Frankel 2000). The resulting focus on supply chain management (SCM) has forced managers to rethink their competitive strategies, with many now seeking to "win with data". In fact, many businesses are almost drowning in data and seeking to monetize their assets with data analysis as a means for gaining a competitive advantage (Bean 2021). Novel combinations of data science, data engineering, future looking predictive machine learning and AI driven analytics as well as "big data" are thought to play crucial role the way in which supply chains are managed and designed.

Although all of the mentioned have value, focus in the research is more in the data as a service and also to some extend data as a product which are sold as commodities. Data as a Service content is raw data or results of analysis process which might include AI or not. The offered solution to the customers is service with such as pricing plans, conditions, versioning, attractive name and description to mention a few. One of the fundamental aims is to define data as a service as accurately as possible. The added value is in the data which is packaged into easy to understand, buy and consume data services. It must be noted that journey of a eventually publicly sold data commodities begins from refined data created for internal use. It is expected that data commodities sold to 3rd parties are first refined in some cases for internal and partner usage. After that the data commodities in some cases are published for others to purchase and utilize. Hypothesis is that Data as a Service Commodities will be treated in companies much like APIs. APIs can be categorised into 3 publicity/openness level layers: 1) private/internal APIs, 2) public APIs (commercial 3rd party usage and partners) and 3) open data interfaces.

Currently data is consumed mostly by technically capable data scientists and data analysts. We are already witnessing the lack of such professionals. The same phenomenon has occurred in software developer business with traditional developers. What is common for both is the need for technical skills to use traditional programming environments and tools. Commoditization of the data sources to be used in easy to use non coding skills driven no-code platform is one possible remedy for the situation. This of course requires that both development environments and data commodities are both combined together without friction.

2 Objectives and methods

The research will be qualitative by nature. The methodological foundation for the research lies in the Design Science Research. Objective is to enrich scientific knowledge of data economy related concepts and processes. **Objective is to clarify fundamental yet still vague concepts like Data as a Service and related Developer Experience**. Second objective of the research is to **create toolkit with process model to design data as a service offerings**, the core concepts must be clarified first.

After having an understanding of what the process creates as a whole (Data as a Service) we can turn our focus to consumers and define the experience from their point of view. Focusing on the customer is important since the value creation is always customer dominant as we have discussed above. After we have the result and customer requirements clear we have start building a process model to match service and customer realms. This final result is the Data as a Service toolkit.

Much of the work is exploration and requires close cooperation, co-creation and co-innovation with operands working with data monetization and servitization. Data Economy is a mixture of technology, business and people interacting with each other. The rich phenomena that emerge from the interaction of people, organizations, and technology needs to be qualitatively assessed to yield an understanding of the phenomena adequate for theory development or problem solving.

The research will use semi-structured interviews and participation driven methods to collect data for the analysis. Main objective of the research is two-folded and visible in the research questions as well.

2.1 Research questions

Research is always a journey. Doctoral dissertation related research even more. It is relatively easy to define framework for the research and direction where it is heading. Research questions are connected to the the research methodology as well and in some cases it may precede construction of the conceptual framework of study. A good research question is feasible, interesting, novel, ethical and relevant. Three research questions have been defined:

- **Q1: How to define Data as a Service and what are the characteristics of it?**
- **Q2: What is the Data as a Service eXperience?**
- **Q3: What is the process and needed tools to design Data as a Service commodities with lean and design driven approach?**

2.2 Methods

Design Science Research (DSR) creates and evaluate IT artifact intended to solve the identified organizational problems(Gacenga et al. 2012). Design Science Research (DSR), has been seen to constitute the third form of science "Artificial" in addition to the natural sciences and the human sciences(Al Turki et al. 2013). Bayazit define Design Science Research Methodology (DSRM) as a systematic inquiry which goal is knowledge of, configuration embodiment, structure, composition, purpose, value, and meaning in man made things and systems.(Bayazit 2004)

The Design Science Research Methodology has found a very good ground as a method in the Information Science and Computer Science, because it is a method that works with human, organizational social kind of problem solving through artifact development (Hevner et al. 2004)

DSRM process generally includes six steps or activities (Peffers et al. 2007): (1) identification of the problem, defining the research problem and justifying the value of a solution; (2) definition of objectives for a solution; (3) design and development of artefacts (constructs, models, methods, etc.); (4) demonstration by using the artefact to solve the problem; (5) evaluation of the solution, comparing the objectives and the actual observed results from the use of the artefact; and (6) communication of the problem, the artefact, its utility and effectiveness to other researches and practicing professionals.

For the above reasons the research uses Design Science Research methodology process model (see Figure 4) defined in article A Design Science Research Methodology for Information Systems Research written by Peffers et al.(Peffers et al. 2007).

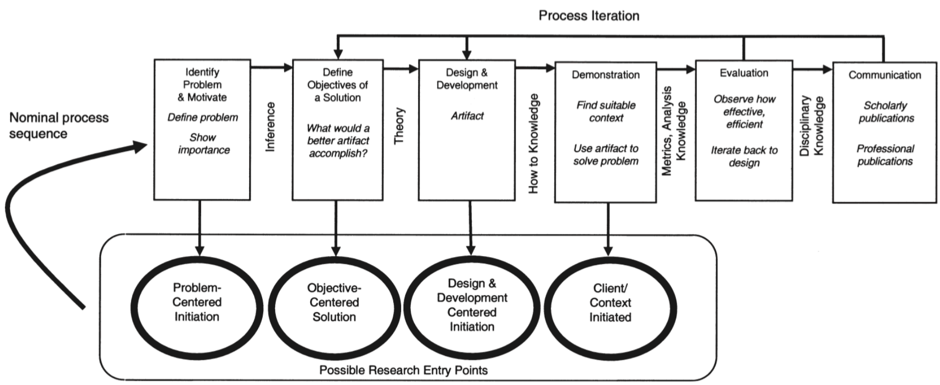

Figure 4: DSRM process model (Peffers et al. 2007)

From the above process we are expected to find common process and methodology which can be applied to similar needs in various organisations and domains. The resulting toolkit can itself act as process to create IS artefact designs.

To define needed concepts (Data as a Service and related developer experience) more thoroughly qualitative methods and analysis is used. More detailed analysis framework and methodology are defined during writing the first articles.

3 Results

3.1 Expected outcomes

What kinds of results are expected?

According to Hevner identify two design processes and four design artifacts produced by design-science research in Information Systems. The two processes are build and evaluate. The artifacts are constructs, models, methods, and instantiations. Purposeful artifacts are built to address heretofore unsolved problems. They are evaluated with respect to the utility provided in solving those problems. (Hevner et al. 2004)

In this research the **main objective is to develop (Q3) a method for designing data as a service commodities and define needed fundamental concepts data as a service (Q1) and related developer experience (Q2)**.

The definitions of the concepts in theoretical level enable more profound dialog about Data Economy and data monetization among scholars and practitioners. The above mentioned method to design Data as a Service commodities is in practise a set of design oriented tools, canvases and checklists with derived data models which can act as input for data as a service platforms. To be able to follow customer need driven process and design data as a service from data value chain perspective a set of new tools are needed. Thus a set of canvases will be developed to be used in practical work.

3.2 Practical relevance

Practical relevance of the expected results (How to apply the results?)

Standardizing the development process makes it faster, requires less resources and learning. Data as a service toolkit and surrounding process model will offer practical tools to do data commodity design from business and service perspective. Process can be utilized by various data monetization engaging organisations and there is no need to reinvent the wheel. Organisations can use the toolkit as is or modify it to fit in their circumstances. The Toolkit is the foundation for further service development. Based on the model and processed defined in the research practical canvases and online tools can be developed for business developers.

Understanding of the developer experience related to data as a service commodities will help the business developers to understand the customer in much deeper level. Defining a framework for the developer experience will remove the need to reinvent the wheel again and again. Furthermore, defining initial framework offers a starting point for other researchers interested about the subject. The defined framework helps the marketing people to understand the target customer and thus make the marketing messages for accurate and to the point.

3.3 Format

Result is a compilation dissertation (introduction + collection of scientific articles).

4 Timetable

4.1 Main phases

During 2021 gather necessary information for two first articles and coauthor at least one of the articles for publication. Aim is to publish first 2 articles during 2022.

Practical action research around the design process and required tools is expected to take place 2022-2023 and third article is published. Analysis of the action research results and tools development will occur 2023 as well as testing of the tool in practical customer cases. The results of the tests and about the toolkit will be coauthored to a publication during 2024.

4.2 Publication plan

Research for two of the articles listed below (bolded) is already proceeding forward.

Article working title	Publish date
Data Economy Focused Developer eXperience Model	1/2022
Data as a Service concept	6/2022
Data as a Service Business Models	6/2023
Rapid Design Driven Data Service development model	1/2024

4.3 Active and expected research activity

At the moment one article is proceeding to research phase: "Data Economy Focused Developer eXperience Model". Coauthors are both from Solita. Antti Loukiala is from Solita Sweden and is working on data science and data analytics driven customer solutions. Timo Lehtonen is from Solita Finland and works in customer cases for maritime safety which is highly data and AI driven. Our joint interest is the needs and expectations as well as cognitive framework of the data as a service primary consumer.

Second article "Data as a Service concept" is also ready to proceed to the next stage. Both of the articles have qualitative approach and will include semi-structured interviews with same target group: data analysts and data scientists. Thus it is expected that we can collect data to both articles with the same interviews by including two parts in the interviews.

5 Resources and collaboration

5.1 Relations to ongoing research

The topic fits well in the agenda of existing research group ”Value Creation for Cyber-Physical Systems and Services”. After having a few discussions with Prof Tuure Tuunanen, it became obvious that this is the group I would fit in.

5.2 Research collaboration network

Currently research network contains individual people and interest group aiming for research project around servitized data. The interest group contains Professors from University of Helsinki (Tommi Mikkonen) and Univerity of Tampere (Hongxiu Li). The mentioned proceeding articles are part of this activity. Three of us (me, Loukiala and Lehtonen) decided to go forward even if a project is still missing.

In addition, constant discussions with Professor Paavo Ritala from the Technical University of Lappeenranta have been going on since 9/2020. Initially one option was to find a home for this research in the Lappeenranta community, but Jyväskylä seems to provide possibly better fitting research community for the topics in this research. Thus Prof Ritala has been guiding my work initially.

5.3 Other collaboration network

I have started biweekly meetings around data economy with a group of people from private sector and public sector. We intend to grow this group into Data Economy Think Tank to offer us common ground for discussions between academic interests and practical cases.

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