UNIVERSITY OF TURKU
Turku School of Economics

Productization of Industrial Analytics Services

How can technology solution and service companies offer scalable analytics services?

Information Systems Science
Bachelor's thesis

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18.5.2026
Turku

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Bachelor's thesis

Subject: Information Systems Science
Author: Kasperi Paassilta
Title: Productization of Industrial Analytics Services
Supervisor: M.sc Tarja Matikka
Number of pages: 33 pages (+1)
Date: 18.5.2026

Abstract

Industry 4.0 and its use of Industrial IOT technologies have led to manufacturing companies using analytics in their processes. Analytics are used for many use cases like reporting and predictive maintenance. There are clear benefits for companies to use analytics in their functions. Large-scale adaptation and scaling have caused challenges, especially for small and medium size firms stemming from technological barriers, high costs, and lack of talent available for these firms. To combat these challenges, firms may use outside service providers to help them achieve their goals with industrial analytics. Servitization of manufacturing industry and the emergence of Product-service-systems has caused more companies to offer services like analytics in companion with their physical products. The companies offering these services have their own challenges with scaling their analytics service offerings due to the complex nature of the services. Service productization refers to transforming services to be like products. A highly servitized product is easy to comprehend and thus easier for the customer to buy. Service productization brings a lot of benefits for both service providers as well as the customer.

These thesis studies how Product-service oriented firms could scale their offerings of industrial analytics services by using service productization methods. Research answers three research questions. How manufacturing industry uses analytics services? What are the benefits of service productization? How can analytics services be productized?

The study is conducted as a literature review researching articles with the key themes of industrial analytics and service productization.

According to the results service productization has a wide range of benefits and could be used to scale analytics services for manufacturing industry if the services offered are targeted to capture wide market adaptation. Productized analytics services could be offered as Analytics-as-a-Service products that combine Software, platform, consulting and infrastructure services.

Keywords: Industrial analytics, Industry 4.0, Service productization, IOT, AaaS

Kandidaatintutkielma

Oppiaine: Tietojärjestelmätiede
Tekijä: Kasperi Paassilta
Otsikko: Teollisten analytiikkapalvelujen tuotteistaminen
Ohjaaja: KTM Tarja Matikka
Sivumäärä: 33 sivua (+ 1)
Päivämäärä: 18.5.2026

Tiivistelmä

Neljäs teollinen vallankumous (Industry 4.0) ja teolliset IOT teknologiat ovat johtaneet siihen, että valmistavan teollisuuden yritykset käyttävät analytiikkaa laajasti osana prosessejaan. Analytiikkaa käytetään monilla eri tavoilla kuten raportoinnissa ja huoltojen ennustamisessa. Analytiikan käytön hyödyt ovat selkeät, mutta niiden laajassa käyttöönotossa on paljon haasteita erityisesti pienillä ja keskisuurilla yrityksillä. Haasteet johtuvat teknologiarajoitteista, kustannuksista ja osaamispulasta. Haasteiden selvittämistä varten moni yritys on alkanut käyttämään ulkopuolisia palvelutarjoajia saavuttaakseen tavoitteensa teollisessa analytiikassa. Teollisuuden palvelullistuminen ja ”tuotepalvelu järjestelmien” synty on johtanut siihen, että fyysisiä tuotteita tarjoavat yritykset ovat alkaneet tarjoamaan palveluita fyysisten tuotteiden rinnalle. Myös palvelutarjoajilla on haasteensa analytiikkapalveluiden skaalaamisessa johtuen palveluiden monimutkaisuudesta. Palvelutuotteistaminen tarkoittaa sitä, että palveluista tehdään tuotteen omaisia. Tuotteistettu palvelu on helppo ymmärtää asiakkaiden toimesta ja on siten helpompi ostopäätös. Palvelutuotteistaminen tuo monia etuja niin palvelutarjoajalle, kuin asiakkaillekin.

Tämä tutkielma tutkii, miten tuote-palvelu-yritykset voisivat skaalata teollisia analytiikkapalveluita hyödyntämällä palvelutuotteistamista. Tutkielma vastaa kolmeen tutkimuskysymykseen. Miten teollisuus käyttää analytiikkapalveluita? Mitä ovat palvelutuotteistamisen hyödyt? Miten analytiikkapalveluita voisi tuotteistaa?

Tutkielma on toteutettu kirjallisuuskatsauksena. Valitut artikkelit liittyvät teolliseen analytiikkaan ja palvelutuotteistamiseen.

Tulosten perusteella voidaan todeta, että palvelutuotteistaminen sopii laajalle markkinalle tähtääville palveluille. Tuotteistetut analytiikkapalvelut voisivat muodostua eri palveluja kuten ohjelmisto-, infrastruktuuri- ja konsultointi palveluja yhdisteleviin Analytics-as-a-Service paketteihin.

Avainsanat: Teollinen analytiikka, Industry 4.0, Palvelutuotteistaminen, IOT, AaaS

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1 Introduction

Manufacturing industries have developed and streamlined their operations to boost their productivity. Most manufacturers have not been using their own data to its full potential. The generated data volumes from process industries are enormous but the companies are not using the data to achieve potential intelligence. The use of analytics to maximise productivity needs advanced analytics and IT expertise that companies lack. To apply analytics to the manufacturing process domain expertise is also needed from manufacturing subject matter experts Because implementation of advanced analytics in manufacturing is challenging for the manufacturing companies, the market opportunity has opened for the manufacturing service and technology companies. The problem they face is the scaling of their analytics service offerings. (McKinsey & Company, 2017).

Digitalization and business models have impacted manufacturing and service companies to evolve their strategies into integrated product-service systems (PSS). Use of digital technologies like Big data-analytics have been a driving factor in the transformation to PSS business ecosystems. (Li et al., 2023). Productization enables service offering to be more professional, effective and profitable. Productised services are easier to communicate to the customers when they are designed according to customer needs and not according to companies' processes. Productization offers solutions to develop services and service companies but there is a lack of research in the subject. (Shamsuzzoha et al., 2024.) There is only a little research done around service productization in the manufacturing space and in manufacturing analytic services.

This thesis is a literature review on articles related to service productization, industrial analytics and analytics services to broader the knowledge about productization of industrial analytics services. The goal is to better understand the field of industrial analytics and to find practical implication of how a technology solution and service firms could better offer industrial analytics services through productised services. Research is conducted with the following research questions.

How manufacturing industry uses analytics services?

What are the benefits of service productization?

How can analytic services be productized?

First chapter will cover the topics related to manufacturing analytics and explains the main themes of Industry 4.0 and different cloud computing service models. This chapter also covers the challenges faced by manufacturing industry's use of analytics and how services are used to mitigate these challenges. The second chapter goes into service productization and its benefits. The third chapter covers scaling strategies for industrial services and drivers behind scaling analytics. It introduces the concept of Analytics-as-a-Service and a framework for companies trying to pursue scalable industrial analytics services.

This thesis will focus on developing service offerings of companies that offer services and technology solutions to manufactures to find out strategies of scaling their industrial analytics services. Focus will be on cloud-based services and not on maintenance services directly.

2 Industrial analytics

Manufacturing industry's digitalization and the use of sensor technologies have enabled companies to implement data collection and analysis across production systems. Manufacturing companies can leverage data analytics for multiple purposes like process optimization. For manufacturing companies to stay competitive they need to use data effectively within the organisations and across the wider markets. (Stahmann & Janiesch, 2026.) Data analytics as term refers to technologies that are mostly grounded to data mining and statistical analysis. Data analytics technologies rely for the most part on relational data warehousing. Data analytics using statistical theories and models have been used successfully in different business applications. The ability to get and communicate actionable insights from raw data to domain experts is emphasized due to the importance of well informed and fact-based decision making. (H. Chen et al., 2012.)

Business analytics refers to reporting and analysing data to find trends and create predictive models with the goal of predicting future problems and opportunities and analysing and optimizing the business and organisations performance. Descriptive analytics or business reporting informs what has happened or what is happening. Predictive analytics discovers patterns and trends to answer what is going to happen or why. Prescriptive analytics is used as support for managers to make decisions based on data analysis. (Delen & Demirkan, 2013.)

Industrial analytics refers to using Industry 4.0 analytics and data-analytics in industrial value creation (Gröger, 2022). With the rise of Industry 4.0 the role of data analytics has become an integral part of industrial management. Leverage of historical data and predictive analytics allows managers anticipate market trends, optimize resources and improve efficiency of operations. Use of data analysis for forecasting maintenance needs helps to avoid unexpected downtimes thus leading to cost savings. Analytics can also be used in identifying segments or production processes that are underperforming to find strategies to optimize them leading to significant improvements in cost savings and productivity. (Abreu & Leite, 2025.)

The following segments cover the technological paradigms behind industrial analytics (Industry 4.0 IoT, Cloud Computing) and studies the use cases and challenges of industrial analytics to better understand the field to possibly find the opportunities where service productization practises could be applied to achieve scalable solutions for industrial analytics services.

2.1 Technologies of industrial analytics

Industry 4.0 refers to the practise of taking advantage of the interconnected world across the value chain using data to optimize the industrial process by creating relevant knowledge from actors of the value chain. In the Industry 4.0 paradigm three characteristics can be identified; "Horizontal integration across the entire value network", End-to-end engineering across the entire product life-cycle" and "Vertical integration and networked manufacturing systems". (Peres et al., 2018.)

Industrial Internet of things (Industrial IOT) refers to industrial systems of sensors and instruments connected over the Internet with multiple use cases such as production, supply chain and energy management. Industrial IOT technologies in manufacturing industry are used to gather, process and handle data. Industrial IOT applications are usually built to be scalable architectures with multiple layers: device layer, network layer, service layer and content layer. The service layer coverts data to knowledge using software and IT applications. Service layer derives the data from the physical components of the device layer and the network layers cloud computing and networking protocols. IOT's data has enabled manufacturers to identify problems and streamline and optimise processes. IOT is mainly used in supply chain management. (Sahoo, 2022.)

Cloud computing refers to an information technology service model of delivering computing services on demand to customers with a self-service over a network independently of device and location. Cloud computing allows users to avoid significant initial capital expenditures with them only paying for the service as an operating expense. The required resources of service are shared with minimal interaction with the service provider. Cloud computing has been identified to multiple key advantages in the business perspective. Cloud computing lowers the entry cost for smaller organisations to take advantage of compute-intensive business analytics. It also provides access to hardware resources almost instantly without the need for upfront capital investments. Use of cloud computing has the possibility to lower IT barriers of innovation. Scaling services becomes easier using Cloud Computing due to the management of computing resources with software. Cloud computing also enables the creation of new applications and services that were not previously possible. (Marston et al., 2011.) Cloud computing is an inseparable part of Industrial IOT. Cloud computing is used to store and process data from manufacturing process to disseminate metadata information across the value chain including different functions and partner organisations. Cloud computing services architectures are organised into three distinct service models: Software as a service (Saas), platform as a service (Paas) and infrastructure as a service (IaaS). With Industrial IOT arises great opportunities for cloud technology platforms to bring value proposition mechanism with the use of sensing algorithms, computing monitoring frameworks and distributed cyber-physical device networks. These can be used to enable real-time processing of analytics and data sharing in the manufacturing sector to boost productivity and performance. The intentions of integrating cloud computing is to build real time efficient communication scenarios with the goal to achieve automation and information streams between different functions in the value chain. (Sahoo, 2022)

Software as a Service (Saas) refers to a service model where customer specific configurations to the applications code could only be made at the metadata layer sitting on top of a common code using interfaces provided by the vendor. In SaaS applications and infrastructure are shared across customers and SaaS constrains customer options to customize software's main functionality and data structures. In addition, SaaS offers the vendor the possibility to control future development of the service leading to customers having to acquire the upgraded service due to the interfaces not being back compatible. Due not needing to enlarge their data centers capacity for customer specific investments, vendors are able to achieve significant economies of scale. (Benlian & Hess, 2011.) Platform as a Service (PaaS) refers to a service model in which development and deployment of applications is enabled without the cost and complexity that comes with managing and buying the underlying hardware and software layers. Third option to provide cloud computing services is Infrastructure as a Service (IaaS). IaaS is a service model where the computing infrastructure and storage is offered as service to the customer for their platforms and software. (Marston et al., 2011.)

Data platforms are the technical foundation of industrial analytics data storage and data processing. The traditional storage platform is Data warehouses used for structured data. With more advanced analytics and the use of unstructured data has the concept of data lakes emerged. (Gröger, 2022.) Data Lake refers to data architecture where the functionality of stored raw data is provided through metadata descriptions that allow users then query data sets for uses cases. The raw data stored in data lake comes from heterogeneous sources. (Hai et al., 2016.) Current industry trends are leading companies to adopt data management architectures combining Data warehouses and Data lakes into integrated data platforms where data warehouses are used as the service layer for the undelaying data lake where the raw data is stored (Gröger, 2022).

2.2 Use cases of industrial analytics

Industrial analytics value creation is achieved through exploiting data to realize data-driven products and services and to develop data-driven processes. Industrial analytics encompasses both traditional descriptive analytics and more advanced analytics like data mining and machine learning. Descriptive analytics mainly focus reporting like key performance indicators (KPI) through enterprise resource planning (ERP) data. The more advanced analytics are used for functions like predictive machine maintenance, predictive process quality and product development. (Gröger, 2022.) In addition, analytics is used in Supply Chain Management, Service Management and in Sustainability management encompassing both Environmental and Social sustainability (Sahoo, 2022).

The technologies of Industrial IoT and big data allow the manufacturing companies to reduce their maintenance budget (Fila et al., 2020). Using analytics in predictive machine maintenance the goal is to avoid unplanned downtime and unnecessary maintenance. In practise it is achieved by using data mining and machine learning to generate prediction models that predict the machines remaining operating time and possible failures to optimize the maintenance cycles according to maintenance data. (Gröger, 2022.) Hosting platforms of data mining and cognitive learning algorithms through cloud computing paradigm allows the delivery of predictive maintenance solution as a service. This kind of service could then be further developed into Service Level agreement (SLA) which allows better quality of service and a pay as you go structure. (Fila et al., 2020.)

Industrial analytics can be used to enhance process quality by using predictive analytics. Using data mining and machine learning to analyse wide range of data enables the identification of root causes of insufficient quality and the forecasting of likely end-of-line quality of parts. Making changes to process based on analytics enables better cost-efficiency. Data used in predictive process quality can include material data, quality data, process data and machine data. (Gröger, 2022.)

Using industrial analytics for product development or “Engineering in the loop” has the goal to improve product design by using real-world product usage data collected by IoT devices like sensors. Next generation of products can be developed when product design, designated usage and real-world usage are compared. If data shows that some product is used differently than it was designed, it can be configured to better meet the real-world use cases. For more advanced analysis can data mining and machine learning be implemented. (Gröger, 2022.)

Business analytics used in critical process like market predictions, procurement and delivery can boost supply chains performance (Trkman et al., 2010). Establishing good relationships between supply chain partners that enables transferring and sharing information across the partner network enhances the Supply Chain analytics capabilities (Cui et al., 2024).

2.3 Challenges with analytics in manufacturing industry

In prior research four factors have been identified as enabling adaptation of big data infrastructure and business analytics transformation in manufacturing organisations; (1)Quality, security and Integrity of Data", (2)Human resource expertise, (3) Scalable technology and (4) Adaption agility. (Sahoo, 2022.) Organisational barriers for adaptation of analytics technologies in manufacturing organisation include concerns with security, limited trust of machine-generated outcomes and lacking insufficient training initiatives (Stahmann & Janiesch, 2026).

If data that is been used to effect business decisions is of bad quality, can it negatively impact the decisions being made. Better outcomes can be achieved if the organisation has the expertise to maintain the quality of the used corporate data. Negative impacts of poor data quality can include customer dissatisfaction, ineffective decision making and reduced ability to make and execute organisations strategy. (Lamba & Singh, 2018.) Scattered data storage, lack of data accessibility between departments, and poor management leads to "data silos" (Junker & Fischer, 2025).

To mitigate the negative impacts of poor data quality management should the data be categorised. Categorising can be done using two dimensions when measuring the data; intrinsic and contextual where intrinsic refers to attributes that are native and objective and contextual referring to attributes that depend on the context of where the data is being used. The collection of data can also cause challenges with data quality. Data from different stakeholders is often collected in different formats and can be unstructured, improper and non-standardized. To solve the problem of homogenous data should the organisations use data warehouses. (Lamba & Singh, 2018.)

To achieve results from big data analytics is a lot of human expertise needed. Because of limitations in organisations analytical capabilities, it can be difficult to convert big data analytics into results. To derive meaningful results from big data analysis does the organisation need qualified human expertise with analytical skills to comprehend the data generated and profound domain knowledge. (Lamba & Singh, 2018.) Insufficient change management can lead to challenges with scaling data-analytics. Especially the business side needs proper onboarding because a good technical solution will not scale if there is no acceptance, willingness or capability to interact with the solution properly. Bottlenecks causing problems with scaling the data analytics operations are also caused due to resource constraints with data analytic roles. (Junker & Fischer, 2025.) Drivers for successful adaptation of analytics in manufacturing organisation relate mostly to employee acceptance of analytics technologies and the development of competitive analytical know-how. For managers this means strategic change management that leads to acceptance and enhances the workforces' competencies. (Stahmann & Janiesch, 2026.) Scepticism of data-driven processes can stem from lack of understanding of technology and the benefits it brings (Abreu & Leite, 2025).

Scalability challenges can be categorized into challenges of scaling the development, challenges of scalable governance and challenges of economical scaling. Challenges for scaling the development related to challenges with data and technology like data silos, data quality and Hard- & software heterogeneity. Challenges with governance relate to problems with capability challenges and fragmentation including insufficient change management, capacity and capability bottlenecks and unit silos. Challenges of economical scaling are Data and analytic business development challenges of high-tech and low-value orientation, transition to hybrid services and stakeholder complexity. (Junker & Fischer, 2025.)

The fast emergence of and evolution of various new digital solutions and solution providers leads to technological challenges with scaling the data analytic processes. The large volume of solutions leads to companies getting confused and lost with technologies which causes complexity in technology management which thus takes more resources leading to hindered development. Technological problems are also caused by the combability problems because of hardware’s and software’s heterogeneity. (Junker & Fischer, 2025.)

Use of big data analytics is expensive. The combination of data capturing and storage technologies, analytic technologies and the talent acquisition of high skilled data experts with the knowledge to get business insights from the big data requires considerable investment. To get require and develop competence for big data analytics needs the top management of the organisation to be committed to the organisational sift and financial burden that comes with the adaptation of big data analytics. The financial support from top management can be an important part of success of the use of big data analytics. (Lamba & Singh, 2018.) Especially Small and medium size enterprises (SME) struggle with the high implementation costs due the high investments needed for technology, infrastructure and skilled labour (Abreu & Leite, 2025).

To mitigate challenges posed by human element in enterprises like employee know-how and acceptance of machine-driven conclusion, can service-based technologies be used to lower the expertise requirements (Stahmann & Janiesch, 2026). To combat challenges of scaling and cost effectiveness of analytics service is service oriented cloud-based solutions a possible solution. Offering analytics services through cloud decreases the unit service costs due to more services being offered and developed. Different data and analytics service offered through cloud can include service models like Analytics-as-a-Service, Information-as-a-Service or Data-as-a-Service. Offered through these services can be data warehouses, analytic processing, end-user components or bundled service products comprised of combinations of different services. (Demirkan & Delen, 2013.) Cloud based services for advanced analytics offer solutions to the accessibility problem faced by especially SME caused by the resource constraint. SMEs can access advanced analytics without the upfront investments to infrastructure provided by services delivered through cloud. Services offered through cloud can include a wide range of functionalities like: real-time processing of data, predictive analytics and advanced visualizations. (Abreu & Leite, 2025.)

2.4 Product service systems (PSS)

To achieve revenue growth in the maternity face of products lifecycle, have the product firms started to seek growth through service offering (Kowalkowski et al., 2017). With the distinction between manufacturing and service companies becoming less defined and the use of technologies like industrial IoT, cloud computing and data analytics in manufacturing industry is leading to the business models of manufacturing and service companies toward integrated product-service systems (PSS). (Li et al., 2023.) Servitization refers to a competitive tool which allows value creation by implementing services into the overall strategy of the firm. In today’s world, servitization is commonly understood to mean service growth in companies mostly offering products. (Kowalkowski et al., 2017.)

To succeed in digitalization as a manufacturing company servitization is needed. Direct impacts on financial performance are achieved with easy-to-implement IT systems when the deployment costs are low. Larger investments should be supported with a higher level of servitization developed through advanced service offering. (Kohtamäki et al., 2020.) Digital servitization refers to the transition toward smart product-service-software systems which are used to create value through digital offerings of products, services and software that function together. In the digital ecosystem the Digital servitization business models are 1) product business model, 2) Industrializer 3) integrated solution provider, 4) outcome provider, 5) platform provider. Companies transitioning to digital servitization can choose between these business models to provide gains. Industrializer refers to an organization which is technology and Manufacturing oriented. In the digital ecosystem their role and business model is to offer modular product offering and service agreements. Industrializers service offering could include services like data driven diagnostics. They find resource efficiency through high modularity. (Kohtamäki et al., 2019.)

3 Service productization.

3.1 Defining service productization

With services being complex and intangible it makes them challenging to position, differentiate and sell in the market (Shamsuzzoha et al., 2024). Service productization (SP) is defined as a process to analyse a need and to define elements into an object similar to a product that is repeatable and comprehendible. Aim of productization is enabling the commercialization of a service to help with its selling, delivery, use and invoicing. In context of services productization is addressing services which are typically abstract and intangible leading to the role of productization being a way to clarify service offering. (Harkonen et al., 2017.) Productizations purpose is the development and reconstruction of services to improve productivity, quality and growth to achieve competitive advantage (Shamsuzzoha et al., 2024).

Productization of services can be achieved through different practises. In the of study productization of professional services has three practises been identified. Practises of productization of professional services are achieved through specifying and standardizing of the service offering, tangibilizizing and concretizing the service offering and professional expertise, and systemizing and standardizing processes and methods. (Jaakkola, 2011.) In addition, modularisation of services clarifies services and decreases their complexity (Harkonen et al., 2017; Shamsuzzoha et al., 2024).

Facilitating the selling and marketing of services needs standardization due the expectation of customers is the offering should be clear and well defined. Dividing the offered service into smaller parts or phases that are easier to standardize enables their easier communication to the customer. (Jaakkola, 2011.) The parts to be standardized are identified to be the repeatable elements that are part of service processes in multiple customer projects (Wirtz et al., 2021). Identifying the core service components and analysing them enables the clarification of core structures of the service components thus eliminating the need to re-invent the elements for each customer (Harkonen et al., 2017). Standardizing service products and service models does not imply no customization. Some parts of service offering are appropriate to standardize but some parts are left open for customization. (Jaakkola, 2011.)
Modularisation in service productization refers to clarifying and services and determining service offering structure. Modularity is used to offer customisation of service products, manage the heterogeneity of services and to help employees understand the rules of combining services in a situation where they are complex. (Harkonen et al., 2017.) Using modular service bundles can be used to specify what the service offering includes and formalizes the value proposition. A complex service can be deconstructed into standardized

pieces which can then be combined flexibly. (Wirtz et al., 2021.) Attributes of modular service include objectification, coordination, complexity management and value co-creation (Harkonen et al., 2017).

Tangibility is important for service businesses due to its relation to how services are understood by the company internally and by customers (Harkonen et al., 2017). By making service tangible refers to making the customer better understand the service. This is due to the understanding that customers perceive buying services a risk because the services seem abstract and don't have clear and easy to understand benefits attached. By offering well productized service products the customer has an easier time to understand what is included with service, when it will be delivered to the customer and what will cost to the customer. When selling a productised service, companies could use terms like "service packages" or "service modules" to make their services more objective. (Jaakkola, 2011.) Tangibility can be achieved through defining and describing service processes, creating basic structures and processes that support tangibility. Supporting tangibility can be done the process of modularity. (Harkonen et al., 2017.) To support tangibility of service products, it is good to define the service offering to a recognisable by developing branding (e.g. brand names and logos) Service products pricing should be tangible as well. Price should be stated upfront and clearly communicated. (Wirtz et al., 2021.)

3.2 Impacts of service productization

Using service productizations principles of standardization, tangibility and modularization to develop service offering brings many benefits and has a positive financial impact. Service productization has a positive impact on service marketing, pricing, process efficiency, work force management, and customer experience enabling both revenue growth and cost efficiency. This section will go into more detail the benefits of service productization and explain the causes of these improvements.

A common case is that service companies seek to increase revenue through offering everything that the customer wants. Operation of this kind cause complexity of the service design makes the control and development of services more difficult. (Shamsuzzoha et al., 2024.) The desired outcome of standardizing is efficient and controllable production processes to combat the individualistic and person-centric professional work (Jaakkola, 2011). Standardizing and modularization of services leads to easier selling and cost effectiveness. Standardization offers solutions to decrease complexity and make the services more tangible, thus making the selling of services easier, leading to increased market share and revenue. Standardized services also allow higher pricing of customisation. (Shamsuzzoha et al., 2024.) Service productization contributes to easing the complex world of selling services through making the services products understandable for salespeople leading positive customer experience. In addition service productization makes service products scalable both internally and across distribution systems. (Wirtz et al., 2021.) Additionally standardization enables measurability that allows comparison between customers. For customer the standardized service helps to assure that procurement of the service could be cheaper than their current situation. (Shamsuzzoha et al., 2024.)

Productization practise of tangibilizing the service has the desired outcome of developing exchangeable service offerings solving the problem of the abstract nature of professional services (Jaakkola, 2011). Tangibilization helps services branding by making the service mentally understandable and recognisable (Wirtz et al., 2021).

Modularisation has multiple benefits relating to service productization. Use of innovative offerings developed by reusing and variating already existing services enables the creation of market impact and service innovation because using insufficient modularised services causes poor innovation. (Harkonen et al., 2017.) Modularisation impacts positively cost efficiency and performance. Using modular services makes establishing the service for customers quicker, leading to decreased set-up times lowering costs. (Shamsuzzoha et al., 2024.)

Across all productization practises does service productization offer clarity of services that leads to better control of services and internal manageability. If services are perceived as adequate can the earning logic and communication be clear. Additional benefit from service productization is the ability to promote the cost-effective tailored services that meet needs and clarify the customer interaction. (Harkonen et al., 2017.) A productised service allows the use of flat-rate pricing for the standard service. For more customised solutions achieved through modular service structures is the price adjusted accordingly. When the pricing is standardised, it is possible to achieve higher margins. Standardized service also allows higher pricing for customisation of services that are more profitable. (Shamsuzzoha et al., 2024.)

Service productization has also implications to work force management. With a standardized service structure is the rotation of work force easier because the service is not depended on individuals. When work becomes more teamwork centric enabled by modular service structure can work satisfaction improve and teamworking can lead to increased motivation. Additionally, rotating the possibility of job rotation increases satisfaction with work. Standardised services also enable increase in company’s knowledge and competence with the reliance of on customer specific knowledge decrease. (Shamsuzzoha et al., 2024.)

Some drawbacks of service productization have also been identified. For firms offering creativity and highly customised and individualized services as their value proposition might service productization not be the best model. Service productization develops the services in to highly scalable to try to capture a wide market so offering them as game changing solutions to for example company's strategic transformation might not seem so authentic. (Wirtz et al., 2021.)

The service productization process and benefits of these processes is formalised in the table below.

Practise	Process execution	Benefit
Standardisation	• Analyse core service components • Divide service into smaller parts that are easy to standardize • Parts are repeatable for multiple projects	• Easier communication to customers • Faster set up times • Cost-efficiency • Higher price for customization
Tangibilization	• Make the service understandable • Clear branding • Clear pricing	• Less abstract • Branding improvements
Modularisation	• Combine standardised service parts into bundles	• Faster set up times • Performance improvements • Service innovation

Table 1. Service productizations benefits for service provider.

4 Productization of analytic services

As the previous chapters have shown, the major problem with use of analytics in manufacturing is scaling, and service productization can be used to better scale services. Companies should use As-a-Service (aaS) type solutions to achieve scalability and flexibility in analytics capabilities. Using aaS type solutions can manufacturing companies introduce new analytics tools gradually without the resistance from sceptical employees. AaS-solutions also offer ease with navigating the complex world of regulatory demands and compliance costs. (Stahmann & Janiesch, 2026.) This chapter studies how analytics can be scaled and how service productization could be used in scaling. The chapter will also offer insights to Analytics-as-a-Service (AaaS) as a possible service model for productized analytic services.

4.1 Scaling industrial analytics and digital services

Junker and Fischer (2025) have identified key challenges and enablers of scaling for data analytics development. Key challenges include the aforementioned: data and technology challenges and challenges of capability and fragmentation and business development challenges. The key enablers of scaling data analytics that have been identified are:

- Unify data foundation and enable fast data access
- Centralize, support and focus
- Educate business and standardize practice
- Empower development workflows and toolkit
- Empower and connect capabilities
- Embrace user & business-centricity

In Junker and Fischer's research (2025) they claim that scaling data and analytics use cases and initiatives are driven by push or pull factors. Push factors refer to integrating the idea of scaling into already existing projects or processes. Pull factors refers to approach where self-initiated discovery of scaling opportunities are encouraged. (Junker & Fischer, 2025.) Scaling digital service causes an internal transformation within the firm. Adopting scaling in early stages of service development leads to long-term scaling opportunities. (Garcia Martin et al., 2025.)

Scaling of industrial small tech firms (STF) offering digital solutions for industrial applications can be approached with several unique ways. Two ways to of scaling STFs offering digital solutions are Ecosystem Scaling Strategy and Servitization Scaling Strategy. (Garcia Martin et al., 2025.)

Scaling digital solutions through Servitization Scaling strategy refers to the firm relying on close customer support and customer insights. Growth is achieved through customer driven value creation and focus on the selected customers. Servitization scaling strategy does not fit a quick mass-market adoption and is resource intensive. Servitization helps in scaling because offering ready digital solutions is not enough and service and solution providers need to support their customers because managing partner satisfaction is important for scalability. (Garcia Martin et al., 2025.)

Scaling using Ecosystem Scaling Strategy refers to firms using partners to achieve sustained growth and to continuously develop the offered digital solutions. Competitive advantage is achieved through advanced technology and development of solutions to be part of a larger offering. Focus is more on development of the solution while nurturing of customer relations and distribution is left to the ecosystem partners. Unlike the servitization scaling strategy where competitiveness is achieved through excellent customer support and flexibility. Choosing between the strategies for scaling depends on firm's role in the ecosystem and what their market approach is. If the firm's solution is targeted to be the main solution and the market leader and to go to market with service lead and customer focused way should the firm choose Servitization strategy. If the solution is meant to be complementing some other solution in the ecosystem and the go-to-market strategy is via partner sales, should the firm choose to scale using the ecosystem strategy. (Garcia Martin et al., 2025.)

4.2 Analytics as a Service

The modern manufacturing worlds decision making relies on real time information and organisations struggle with out the needed knowledge and skills. Service oriented models for manufacturing intelligence can offer crucial assets for data, infrastructure and software and platforms. (Corallo et al., 2022.) Analytics-as-as-Service (AaaS) is a business concept that tries to solve the challenges with complexity of model management, development of service-based analytic models and standardizing interfaces between models (Delen & Demirkan, 2013). AaaS is a service offered through different service layer depending on purpose and stakeholders. AaaS can be delivered as SaaS when it represents a software for business end-users in form of reporting or data mining. If AaaS is delivered as PaaS it can be offering help in development of data-analysis in form of data scientist and developers. AaaS could also be delivered with IaaS framework where virtualized resources are provided to host data and to perform analysis. AaaS service products can be classified as archetypes; Visualization as a service, self-service analytics as a service, Analytics Platform as a service, Big data AaaS and Edge analytics as a service. (Naous et al., 2017.)

An example of a service that combines different service levels is Edge analytics as a service. Edge computing is a computing paradigm allowing integration of core capabilities. In edge computing the computing from IoT-devices is processed in physical proximity to the devices. The capabilities include network, computing and storage closer to the equipment. In IoT edge computing is used to meet the requirements of for light weight intelligent manufacturing and provides business agility and bandwidth optimization when compared with traditional methods. (B. Chen et al., 2018.) Edge computing as a service offers specialized infrastructure and storage of data with real-time processing of the data. It allows industry specific business users, data scientists and developers with analysis of streaming data from connected devices. It can provide real time visual analytics to allow the users to make quick actions based on data. In addition it can offer an environment for prescriptive analytics model development and application development based on cloud. (Naous et al., 2017.)

4.3 A framework for scaling industrial analytics services through service productization

Based on literary review of industrial analytics, its challenges, service productization and the scaling drivers of analytics and digital service in manufacturing can a framework be formulated.

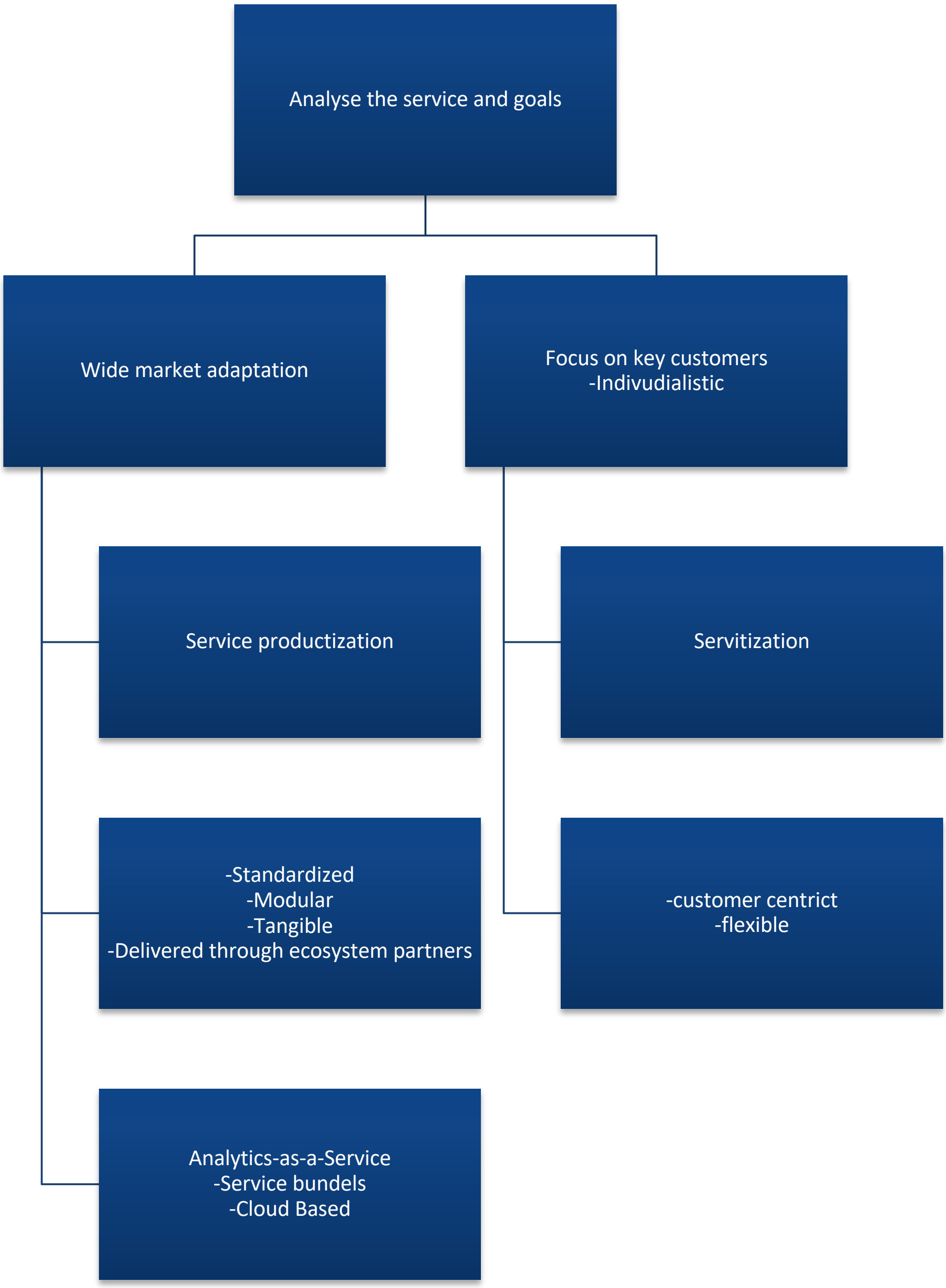

Figure 1. Framework for scaling strategies.

Framework visualises how a technology firms identified to be Industrializers that is trying to achieve service growth in the manufacturing ecosystem should proceed when developing their analytics services based on their role in ecosystem. If firms target is wide capture of the market through generic offering, they should implement practises of service productization to their service development process (Shamsuzzoha et al., 2024). If the service offered by the firm is more complicated and not fit for mass market adaptation should the firm proceed with highly customer centric approach where the customer is involved in the service development process and focus on selected customers (Garcia Martin et al., 2025).

A productized analytics-as-a-service product can be offered on different levels by bundling different cloud-based services (e.g. infrastructure, data processing, end-user software) based on customers current challenges with industrial analytics. All the parts of this service should be highly standardized service modules that are tangible for the customer with clear pricing, branding and ingredients.

5 Discussion and conclusion

5.1 Key Findings

This study investigated the productization of industrial analytics services with the goal of understanding the role that industrial analytics have in modern manufacturing industry and how service productization could be used to develop industrial analytics services towards scalability. Study researched these themes through the following three research questions: (1) How manufacturing industry uses analytic services? (2) What are the benefits of service productization? , (3) How can analytic services be productized?

The rise of technologies like IoT and Cloud computing combined with the servitization of manufacturing industry has led to industrial analytics becoming an integral part of manufacturing industry. Data-analysis based data collected from IoT-devices is used for a wide range of functions to improve efficiency in manufacturing. (Stahmann & Janiesch, 2026.) The use cases of industrial analytics include descriptive analytics like ERP-reporting and more advanced analytics functions like predictive maintenance, product development, process quality management, supply chain management and sustainability management. (Gröger, 2022; Sahoo, 2022.) The challenges faced by manufacturing companies implementing industrial analytics as part of their processes include data quality challenges, workforce capability challenges, high cost of industrial analytics and scalability. (Sahoo, 2022; Stahmann & Janiesch, 2026.) To mitigate the challenges, have manufacturing companies opted to use service providers to help with industrial analytics. Cloud based solutions for can ease the implementation of industrial analytics by lowering the investment costs of infrastructure and expertise and help with workforces' acceptance of machine-driven information. (Abreu & Leite, 2025; Demirkan & Delen, 2013; Stahmann & Janiesch, 2026.) Industrial analytics services can be delivered through different cloud computing paradigms like, SaaS, PaaS, IaaS or more specific solutions like Analytics-as-a-Service or information-as-a-service. Service offered can include visualizations, real-time processing of data, data-storage solutions or combinations of different services. (Abreu & Leite, 2025; Demirkan & Delen, 2013.) To conclude the key finding this research claims that Industrial analytics services are used through cloud-based solutions to mitigate the challenges related to the implementation of Industrial Analytics like investments costs and human challenges.

Service productization refers to service development process where complex service offerings are made to resemble product like offering. A productized service is standardized, tangible and modular. Value creation is achieved through developing services to be understandable and scalable. (Jaakkola, 2011; Wirtz et al., 2021.) A standardized service offers scalability by breaking components into standard modular pieces which can be easily repeated lowering the costs of always tailoring the service to each case. Tangibility of a service refers to service being easy to understand by having it clear to customer what it includes and what impacts it would have for the customer. Elements of tangible service are clear branding and pricing that make the service feel concreate for the customer. (Harkonen et al., 2017; Jaakkola, 2011; Wirtz et al., 2021.)

Service productization has wide impacts on service offering. Benefits of service productization include scalability through repeating the standards components of the service, easier communication to customer leading to easier sales process, increased customer satisfaction, cost-effectiveness of service development and positive impacts on workforce management like increased worker satisfaction. Financial impacts of service productization include increased market share and revenue due to the ease of selling enabled by standardisation and tangibility, lower set up costs, higher margins for customization of solutions. (Jaakkola, 2011; Shamsuzzoha et al., 2024; Wirtz et al., 2021.) Service productization fits best for services that have the intention to capture a wide market and don't need to be highly customized for each customer. If the service offered is meant to be highly complex and have a significant impact on customers operations or organisation might service productization not fit. Service productization offers service providers a wide range of benefits if they want to scale through service ecosystem and provide services for diverse sets of customers. (Shamsuzzoha et al., 2024.)

Scaling analytics services through service productization could offer the benefits of service productization derived through standardization, modularization and tangibility. As-a-service type service products that include bundles of modular services can help to mitigate challenges of Industrial analytics. (Stahmann & Janiesch, 2026.) There is a lack of studies done on using service productization specifically about productization of analytic services thus more research should be conducted to better understand its feasibility and practical execution.

5.2 Practical implications

When Manufacturing technology firms think of service productization as the service model for industrial analytics they should start by evaluating their service, its customers and role in the ecosystem. Service productization does not fit all service types and thus should be used in instances where the goal is wide market adaptation and the service can be easily repeated. (Shamsuzzoha et al., 2024.) Firms that identify as Industrializer (Technology and manufacturing oriented organisation) should offer their services in the digital ecosystem as modular service agreements (Kohtamäki et al., 2019). Making a service productized means developing it to be standardised, modular and tangible. Achieving these goals means developing the service by dividing it into standardised parts that can be modularly connected to each other and developing the service to have a clear brand and pricing structure thus making it understandable to the customer. The service modules could include different types of Cloud based solutions like software or infrastructure that could then be combined into a productised analytics-as-a-Service products.

In the case that the firm evaluate that their service does not fit wide market adaptation and should be focused on selected key customers, is the cookie-cutter type solution of service productization not the right one and development and value creation of the service should be done in close co-operation with the customer. (Garcia Martin et al., 2025.; Shamsuzzoha et al., 2024.)

5.3 Conclusion and Future research

This study provides understanding of Industrial analytics services field and identifies the use case, challenges and how servitization of manufacturing industry effects the field. Study provides ideas of using Service Productization to offer cloud-based Analytics-as-a-Service solutions to achieve scalability with industrial analytics. Industrial paradigms sift towards Industry 4.0 driven by technologies like Internet of things and cloud-computing mean that to stay competitive manufactures need to achieve efficiency using Industrial analytics and service providers could use productized services to better scale their offerings and deliver value to customer because especially SME's face challenges in adaptation of Industrial analytics. Service productization offers cost-efficient solutions for scaling services but it does not fit every type of offering, so service providers need to evaluate their position in the market and the manufacturing ecosystems before proceeding with Service Productization.

Limitations of this study mostly derive from the lack of research done specifically about Service productization in industrial analytics services. To better understand the benefits, challenges and possibilities to do with Productization of Industrial analytics, should it be studied in more detail. The emergence of Artificial intelligence relates heavily to industrial analytics and research into what its implication for the field are should be studied to understand the future of industrial analytics better. More industry specific studies about service productization would expand the knowledge about service productization impacts on different types of services.

References

Abreu, E., & Leite, J. (2025). An Overview of the Opportunities and Challenges of Data Analytics in Industry 4.0: Solutions for a Data-Driven Future in SMEs. *Procedia Computer Science*, *263*, 130–136. https://doi.org/10.1016/j.procs.2025.07.017

Benlian, A., & Hess, T. (2011). Opportunities and risks of software-as-a-service: Findings from a survey of IT executives. *Decision Support Systems*, *52*(1), 232–246. https://doi.org/10.1016/j.dss.2011.07.007

Chen, B., Wan, J., Celesti, A., Li, D., Abbas, H., & Zhang, Q. (2018). Edge Computing in IoT-Based Manufacturing. *IEEE Communications Magazine*, *56*(9), 103–109. https://doi.org/10.1109/MCOM.2018.1701231

Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). BUSINESS INTELLIGENCE AND ANALYTICS: FROM BIG DATA TO BIG IMPACT. *MIS Quarterly*, *36*(4), 1165–1188. (83466038). https://doi.org/10.2307/41703503

Corallo, A., Crespino, A. M., Lazoi, M., & Lezzi, M. (2022). Model-based Big Data Analytics-as-a-Service framework in smart manufacturing: A case study. *Robotics and Computer-Integrated Manufacturing*, *76*, 102331. https://doi.org/10.1016/j.rcim.2022.102331

Cui, L., Wang, Z., Liu, Y., & Cao, G. (2024). How does data-driven supply chain analytics capability enhance supply chain agility in the digital era? *International Journal of Production Economics*, *277*, 109404. https://doi.org/10.1016/j.ijpe.2024.109404

Delen, D., & Demirkan, H. (2013). Data, information and analytics as services. *Decision Support Systems*, *55*(1), 359–363. https://doi.org/10.1016/j.dss.2012.05.044

Demirkan, H., & Delen, D. (2013). Leveraging the capabilities of service-oriented decision support systems: Putting analytics and big data in cloud. *Decision Support Systems*, *55*(1), 412–421. https://doi.org/10.1016/j.dss.2012.05.048

Fila, R., Khaili, M. E., & Mestari, M. (2020). Cloud Computing for Industrial Predictive Maintenance Based on Prognostics and Health Management. *Procedia Computer Science*, *177*, 631–638. https://doi.org/10.1016/j.procs.2020.10.090

Garcia Martin, P. C., Koporcic, N., Sjödin, D., & Parida, V. (2025). Scaling strategies for industrial small tech firms: Exploring the market scaling process, barriers, and outcomes. California Management Review, 68(1), 32–54. https://doi.org/10.1177/00081256251374721

Gröger, C. (2022). Industrial analytics – An overview. *It - Information Technology*, *64*(1–2), 55–65. https://doi.org/10.1515/itit-2021-0066

Hai, R., Geisler, S., & Quix, C. (2016). Constance: An Intelligent Data Lake System. *Proceedings of the 2016 International Conference on Management of Data, SIGMOD '16*, 2097–2100. https://doi.org/10.1145/2882903.2899389

Harkonen, J., Tolonen, A., & Haapasalo, H. (2017). Service productisation: Systematising and defining an offering. *Journal of Service Management*, *28*(5), 936–971. https://doi.org/10.1108/JOSM-09-2016-0263

Jaakkola, E. (2011). Unraveling the practices of "productization" in professional service firms. *Scandinavian Journal of Management*, *27*(2), 221–230. https://doi.org/10.1016/j.scaman.2011.03.001

Junker, S., & Fischer, B. (2025). *Scaling Data & Analytics – A Framework Perspective, Practical Implications and Future Research Agenda*. Hawaii International Conference on System Sciences. https://doi.org/10.24251/HICSS.2025.693

Kohtamäki, M., Parida, V., Oghazi, P., Gebauer, H., & Baines, T. (2019). Digital servitization business models in ecosystems: A theory of the firm. *Journal of Business Research*, *104*, 380–392. https://doi.org/10.1016/j.jbusres.2019.06.027

Kohtamäki, M., Parida, V., Patel, P. C., & Gebauer, H. (2020). The relationship between digitalization and servitization: The role of servitization in capturing the financial potential of digitalization. *Technological Forecasting and Social Change*, *151*, 119804. https://doi.org/10.1016/j.techfore.2019.119804

Kowalkowski, C., Gebauer, H., & Oliva, R. (2017). Service growth in product firms: Past, present, and future. *Industrial Marketing Management*, *60*, 82–88. https://doi.org/10.1016/j.indmarman.2016.10.015

Lamba, K., & Singh, S. P. (2018). Modeling big data enablers for operations and supply chain management. *The International Journal of Logistics Management*, *29*(2), 629–658. https://doi.org/10.1108/IJLM-07-2017-0183

Li, A. Q., Lahy, A., Found, P., Kumar, M., & Claes, B. (2023). Developing PSS business ecosystems in the digital era. *Industrial Marketing Management*, *109*, 121–134. https://doi.org/10.1016/j.indmarman.2022.12.017

Marston, S., Li, Z., Bandyopadhyay, S., Zhang, J., & Ghalsasi, A. (2011). Cloud computing—The business perspective. *Decision Support Systems*, *51*(1), 176–189. https://doi.org/10.1016/j.dss.2010.12.006

McKinsey & Company. (2017). Manufacturing: Analytics unleashes productivity and profitability. Retrieved January 22, 2026, from https://www.mckinsey.com/capabilities/operations/our-insights/manufacturing-analytics-unleashes-productivity-and-profitability

Naous, D., Schwarz, J., & Legner, C. (n.d.). *ANALYTICS AS A SERVICE: CLOUD COMPUTING AND THE TRANSFORMATION OF BUSINESS ANALYTICS BUSINESS MODELS AND ECOSYSTEMS*.

Peres, R. S., Dionisio Rocha, A., Leitao, P., & Barata, J. (2018). IDARTS – Towards intelligent data analysis and real-time supervision for industry 4.0. *Computers in Industry*, *101*, 138–146. https://doi.org/10.1016/j.compind.2018.07.004

Sahoo, S. (2022). Big data analytics in manufacturing: A bibliometric analysis of research in the field of business management. *International Journal of Production Research*, *60*(22), 6793–6821. https://doi.org/10.1080/00207543.2021.1919333

Shamsuzzoha, A., Blomqvist, H., & Takala, J. (2024). Service productisation through standardisation and modularisation: An exploratory case study. *International Journal of Sustainable Engineering*, *17*(1), 1154–1172. https://doi.org/10.1080/19397038.2023.2184514

Stahmann, P., & Janiesch, C. (2026). Drivers, Barriers, and Paradoxical Tensions of Data Analytics Use in German Large Manufacturing Companies. *IEEE Access*, *14*, 28303–28319. https://doi.org/10.1109/ACCESS.2026.3666099

Trkman, P., McCormack, K., De Oliveira, M. P. V., & Ladeira, M. B. (2010). The impact of business analytics on supply chain performance. *Decision Support Systems*, *49*(3), 318–327. https://doi.org/10.1016/j.dss.2010.03.007

Wirtz, J., Fritze, M. P., Jaakkola, E., Gelbrich, K., & Hartley, N. (2021). Service products and productization. *Journal of Business Research*, *137*, 411–421. https://doi.org/10.1016/j.jbusres.2021.08.033

Appendices

Appendix 1 AI disclosure

To support this bachelor's thesis AI was used to support research. The AI service used was Scopus AI. The AI was used to support finding articles relating to the research questions, especially to find the foundational documents about each theme.

Examples of prompts used:

"Find me articles about scaling industrial analytic services"

"Find me articles about industrial management using analytics. Use these journals: Decision Support Systems European Journal of Information Systems Information & Management Information and Organization Information Systems Journal Information Systems Research Journal of the AIS Journal of Information Technology Journal of MIS Journal of Strategic Information Systems MIS Quarterly"

The final decision of articles chosen for this thesis was made by the author and all the articles were read by the author. AI was not used to analyse the articles. All text and research on this thesis was written by the author.